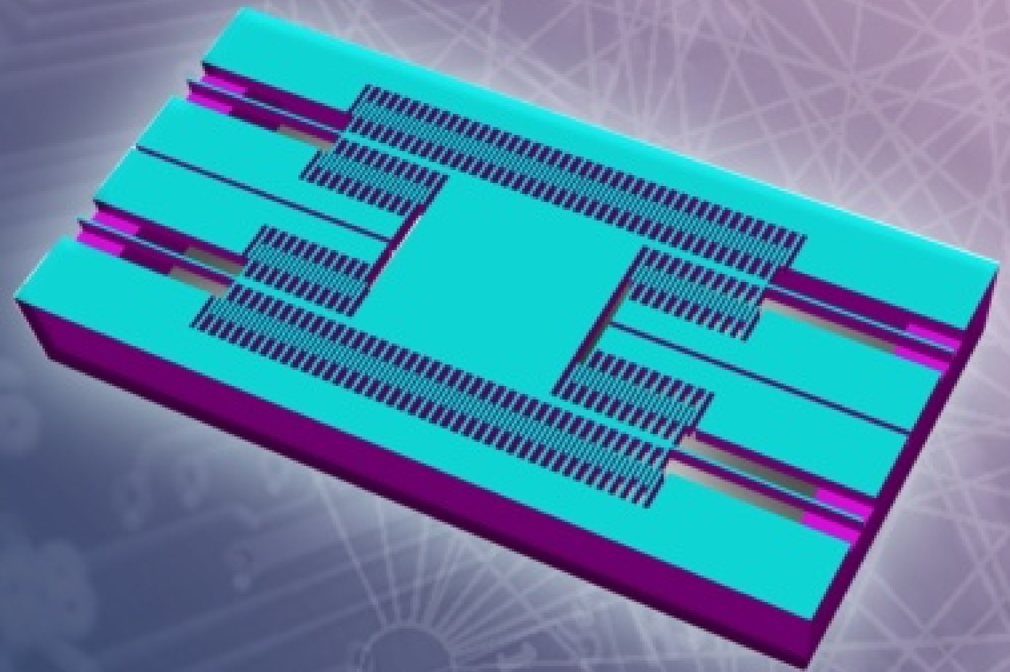
ISSN 1726-5479

SENSORS & TRANSDUCERS

12/12 vol. 17 Special



Sensors and Intelligent Systems

International Frequency Sensor Association Publishing

Sensors & Transducers

Volume 17, Special Issue
December 2012
www.sensorsportal.com
ISSN 1726-5479

Sensors & Transducers Journal (ISSN 1726-5479) is a peer review international journal published monthly online by International Frequency Sensor Association (IFSA).
Available in electronic and on CD.

Sensors & Transducers Journal

Contents

Volume 17
Special Issue
December 2012

www.sensorsportal.com

ISSN 1726-5479

Research Articles

Authors are encouraged to submit article in MS Word (doc) and Acrobat (pdf) formats by e-mail: editor@sensorsportal.com
Please visit journal’s webpage with preparation instructions: http://www.sensorsportal.com/HTML/DIGEST/Submition.htm


IARIA
The Fourth International Conference on Sensor Device Technologies and Applications
SENSORDEVICES 2013
25 - 31 August 2013 - Barcelona, Spain
Tracks: Sensor devices - Ultrasonic and Piezosensors - Photonics - Infrared - Gas Sensors - Geosensors - Sensor device technologies - Sensors signal conditioning and interfacing circuits - Medical devices and sensors applications - Sensors domain-oriented devices, technologies, and applications - Sensor-based localization and tracking technologies - Sensors and Transducers for Non-Destructive Testing
Deadline for papers: 30 March 2013
http://www.iaria.org/conferences2013/SENSORDEVICES13.html


IARIA
The Seventh International Conference on Sensor Technologies and Applications
Deadline for papers: 30 March 2013
SENSORCOMM 2013
25 - 31 August 2013 - Barcelona, Spain
Tracks: Architectures, protocols and algorithms of sensor networks - Energy, management and control of sensor networks - Resource allocation, services, QoS and fault tolerance in sensor networks - Performance, simulation and modelling of sensor networks - Security and monitoring of sensor networks - Sensor circuits and sensor devices - Radio issues in wireless sensor networks - Software, applications and programming of sensor networks - Data allocation and information in sensor networks - Deployments and implementations of sensor networks - Under water sensors and systems - Energy optimization in wireless sensor networks
http://www.iaria.org/conferences2013/SENSORCOMM13.html


IARIA
The Sixth International Conference on Advances in Circuits, Electronics and Micro-electronics
CENICS 2013
25 - 31 August 2013 - Barcelona, Spain
Deadline for papers: 30 March 2013
Tracks: Semiconductors and applications - Design, models and languages - Signal processing circuits - Arithmetic computational circuits - Microelectronics - Electronics technologies - Special circuits - Consumer electronics - Application-oriented electronics
http://www.iaria.org/conferences2013/CENICS13.html

Sensors & Transducers Journal, Vol. 17, Special Issue, December 2012, pp. 98-109

Sensors & Transducers

ISSN 1726-5479

http://www.sensorsportal.com

Development of NO_x Emission Model Using Particle Swarm Optimized Least-Squared SVR (PSO-LSSVR) Hybrid Algorithm

Elangeshwaran PATHMANATHAN, Rosdiazli IBRAHIM, Vijanth ASIRVADAM
Electrical and Electronic Engineering Department,
Universiti Teknologi PETRONAS,
Bandar Seri Iskandar, 31720 Tronoh, Perak, Malaysia
Tel.: +605 368 7821, fax: +605 364 7443
E-mail: elanz117@gmail.com, rosdiazli@petronas.com.my, vijanth_sagayan@petronas.com.my

Received: 29 September 2012 /Accepted: 29 October 2012 /Published: 18 December 2012

Abstract: This paper aims to develop a NO_x emission model of acid gas incinerator using a hybrid of particle swarm optimization (PSO) and least squares support vector regression (LSSVR). Malaysia DOE is actively imposing the Clean Air Regulation to mandate the installation of analytical instrumentation known as Continuous Emission Monitoring System (CEMS) to report emission level online to DOE office. As hardware based analyzer, CEMS is expensive, maintenance intensive and often unreliable. Therefore, software predictive techniques are often preferred and considered as a feasible alternative to replace the CEMS for regulatory compliance. The LSSVR model is built based on the emissions from an acid gas incinerator that operates in a Liquefied Natural Gas (LNG) Complex. PSO is used to optimize the hyperparameters used in training of the LSSVR model. The model is shown to outperform previously developed LSSVR models that were optimized using a combination of Nelder-Mead (NM) simplex and Coupled Simulated Annealing (CSA) algorithms.

Keywords: Industrial pollution, Particle swarm optimization, Predictive algorithms, Support vector machines.

1. Introduction

Power plants, chemical plants, government utilities and petroleum refineries typically produce more than the plant's capacity in order to meet demands. Hence these industries must continuously monitor their exhaust stacks for primary pollutants such as nitrogen oxides, carbon monoxide, sulfur dioxide, and carbon dioxide under regulations promulgated under the New Source Performance Standards (U.S. Environmental Protection Agency (EPA) PA 40 CFR Part 60) or the Clean Air Act Amendments Title IV (40 CFR Part 75) [1] and Malaysian Environmental Quality Act, 1978 [2]. Continuous Emission Monitoring System (CEMS) utilize a sample probe, umbilical and sample conditioning system to extract a representative sample of the stack gas exhaust stream to provide a continuous flow for direct measurement of the pollutant concentration on individual analyzers [3]. A data acquisition system (DAS) is typically used to collect, calculate emission rates, alarm, and store historical data from these CEMS [4]. The promulgated regulations in U.S. EPA 40 CFR covering the monitoring of combustion units for primary and other pollutants allow for the use of predictive emissions monitoring systems (PEMS) in lieu of CEMS. PEMS is a sophisticated software based sensor/prediction system that is directly interfaced with the process control system and inputs from the combustion or pollution control process. The U.S. EPA have revealed the devastating effects of continuous release of carbon dioxide, methane, nitrous dioxide and other greenhouse (heat-trapping) gasses to the atmosphere [5]. Climate change induced by these gases can cause damage to human health, agriculture, natural ecosystems, coastal areas and other climate sensitive systems. Currently, emission monitoring is done via analytical instruments which are very expensive to install and maintain; the cost for an online NO_x analytical and monitoring system is around $100,000 to $200,000 and the cost for maintenance is approximately $15,000 per year [6].

Several works have been done to develop predictive systems for industrial emissions. One of the earlier ideas was presented by Baines [7]; a consultant from Fisher-Rosemount Solutions. Stack contaminants are predicted in real time by correlating emissions with key unit parameters like fuel type, air and fuel flows and combustion temperature. Chakravarthy et al [8] have developed a PEMS for industrial process heaters. Heuristic optimizer genetic algorithm (GA) is used to tune the NO_x kinetic parameters. Zheng et al [9] used generalized regression neural network (GRNN) to establish a non-linear model between the parameters of the boiler (of 300MW steam capacity) and the NO_x emissions. Later, the GRNN model is replaced with the LSSVR model. It is claimed that this new algorithm yields better accuracy of a coal combustion unit [10]. LSSVR regression models of CO_2 and NO_x emissions have been developed previously by the authors using a combination of NM and CSA algorithms as optimizers [11, 12]. The developed models performed significantly better against benchmark back propagation neural network models. The objective of the present work is to improve the performance of previous models by introducing hybrid PSO-LSSVR model. This paper is organized as follows: Section 2 presents a brief literature on LSSVR and PSO. Section 3 describes the modeling background in terms of the parameters used, case study of acid gas incinerator and the dataset used. Section 4 presents the results and analysis and Section 5 gives a brief conclusion.

2. Literature Review

2.1. Least Squares Support Vector Regression (LSSVR)

The foundations of classical support vector machines (SVM) were laid by Vapnik [13]. Early SVMs were developed for classification problems, later it was extended to the domain of regression problems [14] and collectively known as support vector regression (SVR). Classical SVM formulation leads to a quadratic programming (QP) problem with linear constraints. The size of the matrix involved in the QP problem is directly proportional to the size of the training data [10]. To reduce the complexity of the optimization problem, Suykens et al [15] introduced a modified version of SVM called least squares – SVM. LS-SVM formulation results in a set of linear equations instead of a quadratic programming problem. LS-SVM is used for both classification and regression problems. The formulation for LSSVR begins by taking a training set:

$$D = \{(x^1, y^1), \ldots, (x^l, y^l)\}, x \in R^n, y \in R \quad (1)$$

It is to be estimated using a non-linear function:

$$f(x) = w^T\varnothing(x) + b;\ \varnothing(.): R^n \rightarrow R^{nk}, \tag{2}$$

where ∅(.) is the mapping function to a high dimensional and potentially infinite dimensional feature space; in this paper, there are 22 dimensions in the low dimensional space and 484 dimensions in high dimension space. Next, the optimization is formulated in primal weight space:

$$\min \Phi(w,e) = \tfrac{1}{2} w^T w + \gamma \tfrac{1}{2} \sum_{i=1}^{l} e_i^2 \tag{3}$$

Subject to:

$$y_i = w^T \phi(x_i) + b + e_i \quad i = 1,...,l$$

The optimization formulation in Eq. 3 is ridge regression cost function formulated in feature space. Constructing the Lagrangian of the problem, the dual problem is derived:

$$L(w,b,e,a) = \Phi(w,e) - \sum_{i=1}^{l} \alpha_i \{ w^T \phi(x_k + b + e_i - y_{i)\}} \tag{4}$$

The conditions for optimality are given by [15]:

$$\begin{aligned} &\tfrac{\partial L}{\partial w} = 0 \quad \rightarrow \quad w = \sum_{i=1}^{l} \alpha_i \phi(x_i) \\ &\tfrac{\partial L}{\partial b} = 0 \quad \rightarrow \quad \sum_{i=1}^{l} \alpha_i = 0 \\ &\tfrac{\partial L}{\partial e_i} = 0 \quad \rightarrow \quad \alpha_i = \gamma e_i \quad i = 1,...,l \\ &\tfrac{\partial L}{\partial \alpha_i} = 0 \quad \rightarrow \quad w^T \phi(x_i) + b + e_i - y_i \quad i = 1,...,l \end{aligned} \tag{5}$$

Upon elimination of the variables *w* and *e* and solving in *a* and *b* one gets the following solution in dual space:

$$\begin{bmatrix} 0 & 1_V^T \\ 1_v & \Omega + 1/y \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{6}$$

where $by = [y_1;\ldots;y_l]$, $1_v = [1;\ldots;1]$ and $\alpha = [\alpha_1;\ldots\alpha_l]$. The "kernel trick" [16] is applied here as shown

$$\Omega_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j) \quad i,j = 1,...,l \tag{7}$$

Hence the resulting LSSVR model becomes:

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x_i, x_j) + b \tag{8}$$

In this paper, RBF kernel function is used:

$$K(x,x') = \exp\left(- \frac{\|x - x'\|}{2\sigma^2} \right), \tag{9}$$

where α_i and b are the solutions to the linear system represented by Eq. 6. The LSSVR formulation can be used to handle large datasets with no dimensionality problem. In Eq. 7, a kernel function (represented in Eq. 9) is used to replace the high order mapping function. In this paper, the RBF kernel will be used exclusively for all computations involving kernel operations. In the case of RBF kernel, only two hyperparameters need to be tuned (γ,σ) which is less than standard SVM.

2.2. Particle Swarm Optimization (PSO)

The birth of PSO algorithm was inspired by the coordinated and collective behavior of fishes and birds. Fig. 1 shows every particle *i* have a neighborhood N_i. Reynolds [17] introduced a behavioral model where agents follow three rules of separation, alignment and cohesion. Later, Kennedy and Eberhart [18] introduced a 'roost' in a simplified Reynolds-like simulation so that each agent gets attracted towards the roost, remembers where it was closer to roost, and shares information with its neighbors about its location closest to the roost. The distance to roost can be analogous to any minimization function; hence all agents will land in the minimum. PSO has been applied in many research areas such as training neural networks [19], optimization of electric power distribution networks [20], structural optimization [21], and process biochemistry [22]. Basic algorithm proposed by Kennedy and Eberhart [18] is shown below:

- x^i_k : Particle position;
- v^i_k : Particle velocity;
- p^i_k : Best remembered individual position;
- p^g_k : Best remembered swarm position;
- c_1, c_2 : Cognitive and social parameters;
- r_1, r_2 : Random numbers between 0 and 1.

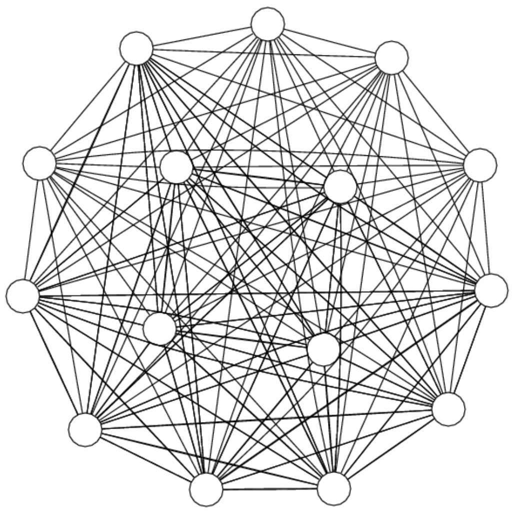


Fig. 1. Every particle i has a neighborhood N_i.

Position of individual particles updated as follows:

$$x^i_{k+1} = x^i_k + v^i_{k+1} \tag{10}$$

With the velocity calculated as follows:

$$v_{k+1}^{i} = v_{k}^{i} + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^g) \quad (11)$$

PSO algorithm flow is as follows:

1) Initialize

(a) Set parameters k_{max}, c_1, c_2,
(b) Randomly initialize particle positions:

$$x_0^i \in D \text{ in } R^n \text{ for all } i = 1,...,p \quad (12)$$

(c) Randomly initialize particle velocities:

$$0 \le v_0^i \le v_0^{max} \text{ for } i = 1,...,p \quad (13)$$

(d) Set $k = 1$

2) Optimize

(a) Evaluate function value f_k^i using design space coordinates x_k^i.
(b) If $f_k^i \le f_{best}^i$ then $f_{best}^i = f_k^i$, $p_k^i = x_k^i$
(c) If $f_k^i \le f_{best}^g$ then $f_{best}^g = f_k^i$, $p_k^g = x_k^i$
(d) If stopping condition is satisfied, go to 3, else.
(e) Update all velocities v_k^i for $i = 1,...,p$
(f) Update all positions x_k^i for $i = 1,...,p$
(g) Increment k
(h) Go to 2 (a)

3) Terminate

Some of the weaknesses that were found in the classical PSO algorithm are weak exploitation of local optima and premature convergence. Several modifications were put forward; Shi and Eberhart [23] introduced an inertia term (w) in velocity rule:

$$v_{k+1}^{i} = w_k v_{k}^{i} + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^g) \quad (14)$$

$$w_{k+1} = \alpha w_k, \quad 0 < \alpha < 1. \quad (15)$$

A modified term for inertial weight that changes dynamically with each iteration could also be used:

$$w_{k+1} = \left[\frac{w_{final} - w_{init}}{k_{max} - 1} \right] * (k + w_{init}) \quad (16)$$

Clerc and Kennedy [24] later proposed a constriction factor (K) which modifies the velocity rule to:

$$v_{k+1}^{i} = K [\ v_{k}^{i} + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^g) \quad (17)$$

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4}\right|}; \quad \varphi = c_1 + c_2 \tag{18}$$

In order to keep the particles from moving too far beyond the search space, a technique called velocity clamping is used to limit the maximum velocity of each particle [25]. For a search space bounded by the range [x_{min}, x_{max}], velocity clamping limits the velocity to the range [v_{min}, v_{max}].

3. Modeling Background

3.1. Nelder-Mead LSSVR

In the previous work by the authors [11], LSSVR model was developed using NM and CSA as its optimizer. This model will be represented by the acronym NMCSA-LSSVR. NM algorithm is nicknamed the "amoeba" due to its biological-like search patterns. In 2-D, it consists of a search-triangle or "crawler" or "simplex" with three points that represent the highest (worst) point, next highest point and the lowest (best) point. The intuition is to move away from high point towards the low point. The simplex moves in several transformations that are known as "reflection", "contraction", "reflection and expansion" and "multiple contractions" to find the optimal value for the minimization problem [26]. The parameter settings for the simplex algorithm are shown below:

- Expansion steps = 2
- Size of initial simplex = 1.2
- Contraction steps = 0.5
- Reflection steps = 1
- Shrinkage steps = 0.5
- No. of optimization steps = 200
- No. of function evaluations = 50
- Stopping criterion based on value of function = 1e-6
- Stopping criterion based on change in minimizer = 1e-6

The initial values of the hyperparameters (γ and σ) is found using SA. This technique is borrowed from metallurgy where it is a global optimizer for a large search space. SA is designed to find an optimized solution in a given time, rather than finding the best possible solution [27], this saves computation time and it is suitable for finding initial values for further optimizations. SA parameter settings are as follows:

- Initial temperature = 1
- Max no. of function evaluations = 40
- No. of steps at fixed temperature = 20
- Energy tolerance = 1e-45

3.2. PSO-LSSVR

In this current work, an LSSVR model is developed using PSO as its optimizer. Parameter selection guidelines for PSO optimizer have been outlined by Trelea [28]. The number of iterations is a function of the admissible computation time and the complexity of the cost function. Its selection is important to ensure quick convergence and equilibrium of the particles. The random number in the PSO algorithm amplifies zigzagging tendency and slows down convergence, hence improving state space exploration and preventing premature and non-optimal convergence. Additionally, Trelea stated that the convergence of the algorithm is also influenced by the number of particles in the swarm N (bigger swarm needs more iterations to converge) and by the topology; strongly connected swarms converge faster than loosely connected ones. The best tradeoff between exploration and exploitation depends on the function that is being optimized; number of local optima and distance to the global one, position of the global minimum in the search domain, size of the search domain, required accuracy, etc. Carlisle and Dozier [29] conducted several experiments to determine optimal values for PSO parameters for various optimization problems. Among others, it was found that a population size of 30 appears to be small enough to be efficient yet large enough to be reliable. Global neighborhood appears to be a better choice compared to small local neighborhood which seems to require less work for the same results. Considering existing literature and current optimization problem at hand, common PSO type with inertia weight is used and the selected parameter values are:

- Max epochs (k_{max}) = 5
- Population size = 25
- Cognitive parameter (c_1) = 2.1
- Social parameter (c_2) = 2.1
- Initial inertia weight (w_{init}) = 0.9
- Final inertia weight (w_{final}) = 0.6
- Min error gradient = 1e-99
- [x_{min}, x_{max}] = [-0.6094 , 2.6094]
- [v_{min}, v_{max}] = [-1.6094, 1.6094]
- Update = Synchronous for both individual best and global best.

3.3. Performance Function

The performances of the models are gauged using standard performance functions in the form of root means square error ($RMSE$) (Eq.19), correlation factor (R) (Eq. 20), accuracy (A) (Eq. 21) and computational time (T_c).

$$RMSE = \sqrt{\tfrac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2} \tag{19}$$

$$R = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(\hat{X}_i - \overline{\hat{X}}_i)}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2}\sqrt{\hat{X}_i - \overline{X}})^2} \tag{20}$$

$$A = 100 - (\tfrac{1}{n}\sum_{i=1}^{n}(\frac{|\hat{X}_i - X_i|}{\hat{X}_i}) \times 100) \tag{21}$$

X_i is the predicted value, $\hat{X}_i$ is the true value and n is the number of testing samples. An overall flow of LSSVR algorithm is presented in Fig. 2.

3.4. Case Study

In this paper, the NO_x emission from a tangentially fired acid gas incinerator is modeled. This incinerator train is part of a LNG complex. The plant is divided into four sections consisting of upstream facilities, gas treating, liquefaction and storage/terminal. The first part of the gas treating section deals with the acid gas in the feed. CO_2 and H_2S are removed to meet product specification. Solvent with absorbed acid gases are regenerated in a regenerator column at high temperature and low pressure. The acid gases are then incinerated before being discharged safely to the environment [30]. The process flow scheme of the incinerator train is shown in Fig. 3. The main constituents of the input to the incinerator are acid gas, flash gas, fuel gas and combustion air. The flue gases that are released to the stack consist of NO_x, SO_2, SO_3, CO, CO_2 and H_2S. In this paper only NO_x emission will be modeled based on plant input and output process variable data. The data is obtained from the LNG complex incinerator train DCS' historical dataset taken from April 2010 to November 2010 and contains the data from 29 input process variables and 7 output process variables. The most relevant process variables are selected by reviewing the design and operational specifications in the incinerator material balance sheet. Initial correlation analysis was also performed to the dataset to determine the variables that have the strongest variance with each other. As a result, 22 input variables and one output variable (i.e. flue gas NO_x content) are chosen with 1068 number of samples, taken at 30 minutes apart for the whole month of October 2010. The number of data points for LSSVR is limited by the computational ability of the machine that is used to run the model. Mainly because the M-file implementation is memory intensive compared to C-Mex or C++ languages. Tables 1 and 2 outline the characteristics of the chosen input and output variables. The relationship between NO_x and the input variables are not easily modeled mathematically (and it is beyond the scope of this paper) and any attempt on graphical plotting shows erratic distributions (which on some level demonstrates a highly non-linear relationship). However the relationship can be proven by correlation analysis and by studying the process flow and material balance of the feed and product gases. Before modeling, data is pre-processed to remove bad inputs and non-values. The SVR model uses 80 % for training and cross-validation and 20 % for testing.

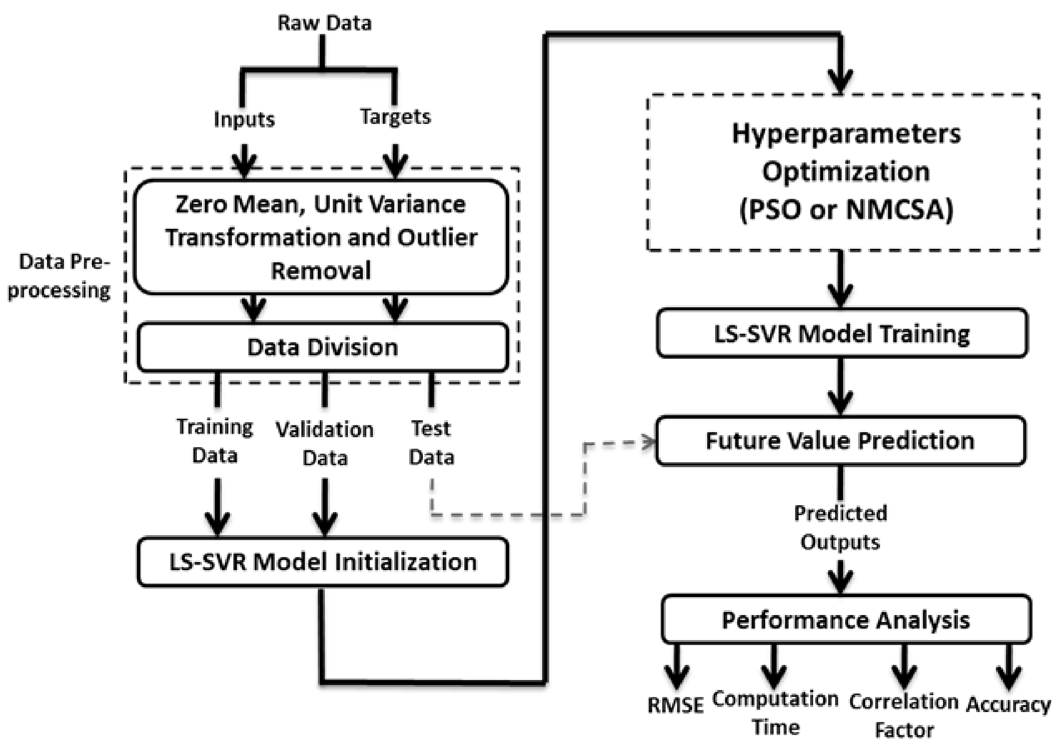


Fig. 2. LSSVR flowchart.

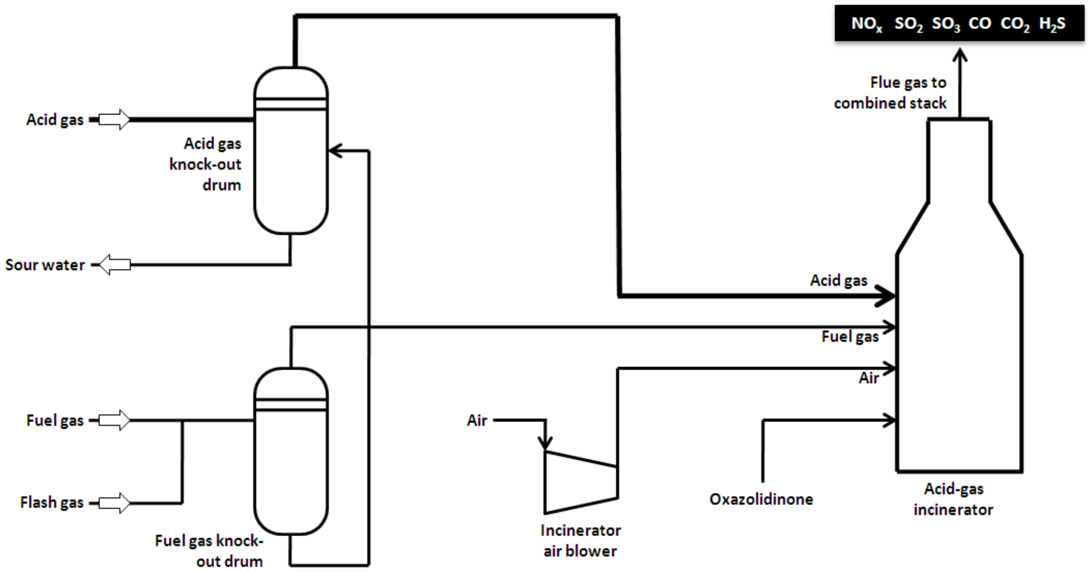


Fig. 3. PFS of incinerator train.

Table 1. Selected input process variable.

PROCESS VARIABLES	ENGINEERING UNITS	OPERATIONAL UNITS
A-91921 SOUR FEED GAS FLOW	T/D	Incinerator Unit 2
FUEL GAS TO A91921	%	Incinerator Unit 2
FUEL GAS TO INCINERATOR A-91921	Density	Incinerator Unit 2
K-91921 SUCTION AIR FLOW	T/D	Incinerator Unit 2
A-91921 STACK EXH TEMP	DEGC	Incinerator Unit 2
A-91921 STACK EXH TEMP	DEGC	Incinerator Unit 2
H2O ANALYSER A	ppm	N/A
H2O ANALYSER B	ppm	N/A
CO2 ANALYSER	%	N/A
H2S ANALYSER	ppm	N/A
C-91101 FEED GAS FLOW	T/D	Flash Gas Unit
CO2 IN WET FEED GAS FR C91101	ppm	Flash Gas Unit
H2S IN WET FEED GAS FR C91101	ppm	Flash Gas Unit
C-91101 TREATED NG TEMP	DEGC	Flash Gas Unit
C-91101 TREATED NG FLOW	T/D	Flash Gas Unit
LEAN SLVT TO C91101 FLOW	T/D	Flash Gas Unit
C-91103 SOLVENT REFLUX FLOW	T/D	Sour Water Unit
HP F/G TO KG91420 FLOW	T/D	Gas Turbine Unit
MR IGV POSITION FEEDBACK	N/A	Gas Turbine Unit
MR TURBINE SPEED	N/A	Gas Turbine Unit
MR COMB REFERENCE TEMP	DEGC	Gas Turbine Unit
MR MWATT ACTUAL POWER	MWATT	Gas Turbine Unit

Table 2. Output process variables (only NO_x is selected for this paper).

PROCESS VARIABLES	ENGINEERING UNITS	OPERATIONAL UNITS
A-91921 FLUE GAS O2 CONTENT	mol%	Incinerator Common Stacks
A-91921 FLUE GAS NOX CONT	mg/nm3	Incinerator Common Stacks
A-91921 FLUE GAS SO2 CONT	ppmv	Incinerator Common Stacks
A-91921 CO CONTENT	mg/m3	Incinerator Common Stacks
A-91921 CO2 CONTENT	%	Incinerator Common Stacks
A-91921 FLUE GAS H2S CONT	ppm	Incinerator Common Stacks
SO3 CONTENT	ppm	Incinerator Common Stacks

4. Results and Analysis

Performance of both models is presented here in terms of correlation, root means squared, accuracy of the predicted values and computational time is also shown in Table 3. Table 4 shows the optimization results from both NMCSA and PSO routines. From Table 3, PSO-LSSVR model performs slightly better than NMCSA-LSSVR model in terms of RMSE and correlation factor (R). The accuracy of both models exceeds the industrial standards for PEMS development, as outlined in US EPA Performance Specification 16 [1]. In the guideline, all PEMS model is required to have an accuracy of at least 90 %, however the accuracy of both models in the current work is more than 96 %. The significant accuracy of the models is attributed to the fact that LSSVR is a 'transparent' algorithm where the resultant model has weights and biases that were optimized to suit the particular dataset. The solutions provided by support vector machines are unique and global in a dual space problem; this is achieved by solving the Karush-Kuhn Tucker (KKT) system at its core. The generalization ability of both LSSVM models are excellent, as a result of its training using cross-validation methods.

Table 3. Model Performances.

		RMSE	R	Accuracy	Computational Time
PSO-LSSVR	**Train Data**	0.2449	0.9852	97.7532 %	39.5677 s
	Test Data	0.4791	0.9436	95.3207 %	
NMCSA-LSSVR	**Train Data**	0.2855	0.9796	97.2740 %	48.9366 s
	Test Data	0.4869	0.9410	95.2160 %	

Table 4. Parameter Optimization Results.

	Minimizer 1 (γ)	Minimizer 2 (σ)	Minimized Cost (MSE)
PSO	5.9451	13.5914	1.9704e-1
NMCSA	46.8909	60.4091	1.7028e-1

SVM algorithms are a kernel based method; hence the complexity is in the order of $O(n^3)$ which means that the computational power and required running time is higher than other modeling algorithms such as artificial neural networks. Nevertheless, the current PSO-LSSVR model has significantly improved the computational time and power requirements of the previously developed model. The current model is 10 seconds quicker. From Table 4, NMCSA and PSO found almost the same minimized cost but using different minimizer values. Although NMCSA found s slightly smaller cost/objective function, it does not mean that it is a better optimizer because the PSO-LSSVR model has better accuracy. This is because the optimizer found minimizer values that are contribute to better overall generalization ability of the model. So, it can be concluded that PSO optimizer is better suited for LSSVR modeling application. PSO has the advantage of being insensitive to scaling of design, simple implementation, easy parallelization for concurrent processing, derivative free, fewer algorithm parameters and efficient global search algorithm. NMCSA algorithm has the advantage of locating local minima more efficiently and comparatively PSOs have slow convergence in refined search (weak local search ability) [25].

5. Conclusion and Recommendations

In a nutshell, this paper has brought to focus the ability to model NOx emissions from an acid-gas incinerator using LSSVR algorithms. The objective of the paper is to improve the performance of previous models by introducing hybrid PSO-LSSVR model. The modeling was done using a series of steps that includes optimization of hyperparameters using PSO optimizer. Preliminary results show that NMCSA is a better optimizer compared to PSO based on the minimized cost function value; however the PSO-LSSVR model performance is better compared to NMCSA-LSSVR model. It is also notable that the PSO-LSSVR model is relatively quicker in computation time. Both of these improvements satisfy the objectives of the paper. The superiority of PSO-LSSVR model can be accounted to the fact that PSO is an efficient global optimizer for continuous variable problems and it is easily implemented with very little parameters to fine tune. Overall, the objectives of the paper have been achieved, and in the future algorithm modifications will be introduced to improve PSO local search ability.

References

[1]. U. S Environmental Protection Agency, Clean Air Act as of 2008. Chapter 85: Air Pollution Prevention and Control. s. l.: *U. S. Government Printing Office*, 2008.

[2]. Environmental Quality (Clean Air) Regulations 1978, Federal Subsidiary Legislation Environmental Quality Act 1974 [Act 127]. s. l.: *Department of Environment*, Malaysia, 2000.

[3]. Fan Xiaoliang, Zheng Haiming, Design CEMS for Flue Gas From Thermal Power Plant, *Asia-Pacific Power and Energy Engineering Conference APPEEC*. Baoding, China, 2009.

[4]. Haiming Zheng, Guiji Tang, Developing Data Acquisition and Handling System for Continuous Emission Monitoring System from Coal-Fired Power Plant, *Chinese Control and Decision Conference CCDC*, Baoding, China, 2008.

[5]. US Environmental Protection Agency, Climate Change - Health and Environmental Effects, *US EPA Home Page*. [Online] [Cited: April 8, 2011] http://www.epa.gov/climatechange/effects/index.html

[6]. Dong, Dong and McAvoy, Thomas J. Seattle, Emission Monitoring Using Multivariate Soft Sensors, in *Proc. of the American Control Conference*, Washington, 1995.

[7]. Baines, Glenn, Neural Networks for Boiler Emission Prediction, s. l: Performance Consultant Fisher-Rosemount Solutions, 1999, pp. 435-439.

[8]. S. S. S. Chakravarthy, A. K. Vohra, B. S. Gill, Predictive emission monitors (PEMS) for NO_x generation in process heaters, *Computers and Chemical Engineering*, 23, 11-12, 2000, pp. 1649–1659.

[9]. Ligang Zheng, Shuijun Yu, Minggao Yu. Jiaozuo Henan, Monitoring NO_x Emissions from Coal-Fired Boilers using Generalized Regression Neural Network, *The 2nd International Conference on Bioinformatics and Biomedical Engineering (ICBBE)*, 2008, pp. 1916-1919.

[10]. Ligang Zheng, HailinJia, Shuijun Yu, Minggao Yu, Jiaozuo Henan, Prediction of NO_x Concentration from Coal Combustion Using LS-SVR, *4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE)*, 2010, pp. 1-4.

[11]. Elangeshwaran Pathmanthan, Rosdiazli Ibrahim, Vijanth Asirvadam, Development of CO_2 Emission Model of an Acid-Gas Incinerator using Nelder-Mead LS-SVR, *Transactions of the Institute of Measurement and Control*, London, UK (in press).

[12]. Elangeshwaran Pathmanathan, Rosdiazli Ibrahim, Vijanth Asirvadam, Development of NO_x Emission Model for a Tangentially Fired Acid Incinerator, in *Proc. of the International Conference on Computer, Electrical and Systems Sciences and Engineering*, Bali, Indonesia, October 2011.

[13]. Vapnik, V. N. Y, The Nature of Statistical Learning Theory, *Springer*, 1995.

[14]. V. Vapnik, S. Golowich, and A. Smola, Support vector method for function approximation, regression estimation, and signal processing, *Advances in Neural Information Processing Systems*, 9, 1997, pp. 281-287.

[15]. J. A. K. Suykens, T. V. Gestel, J. D. Brabenter, B. D. Moor, J. Vandewelle, Least Squares Support Vector Machines, *World Scientific Publishing*, NJ, USA, 2002.

[16]. N. Cristianini and J. Shawe-Taylor, An introduction to support vector machine and other kernel-based learning method, *Cambridge University Press*, Cambridge, 2000.

[17]. Reynolds, Craig W., Flocks, herds, and schools: A distributed behavioral model, *ACM Computer Graphics*, Vol. 21, 4, 1987, pp. 25-34.

[18]. Eberhart, James Kennedy and Russell, Particle swarm optimization, in *Proceedings of the IEEE International Conference on Neural Networks*, Piscataway, NJ, USA, 1995, pp. 1942-1948.

[19]. Eberhart, R. C., and Shi, Y. Beijing, P. R. C., Evolving artificial neural networks, in *Proc. of the Int'l. Conf. on Neural Networks and Brain*, 1998, pp. 5-13.

[20].Fukuyama Y., Yoshida, H. Piscataway, A Particle Swarm Optimization for Reactive Power and Voltage Control in Electric Power Systems, in *Proc. of the Congress on Evolutionary Computation*, Seoul, Korea, 2001.
[21].R. E. Perez, K. Behdinan, Particle swarm approach for structural design optimization, *Computers & Structures*, Vol. 85, 19-20, October 2007, pp. 1579-1588.
[22].A. R. Cockshott, B. E Hartman, Improving the fermentation medium for Echinocandin B production part II: Particle swarm optimization, *Process Biochemistry*, Vol. 36, 7, February 2001, pp. 661-669.
[23].Eberhart., Yuhui Shi and Russell, A modified particle swarm optimizer, in *Proceedings of the IEEE International Conference on Evolutionary*, Piscataway, NJ, USA, 1998, pp. 69-73.
[24].Clerc, M., Kennedy, J., The particle swarm - explosion, stability, and convergence in a multidimensional complex space, *IEEE Transactions on Evolutionary Computation*, Vol. 6, 1, 2002, pp. 58-73.
[25].Bergh, Frans van Den, An Analysis of Particle Swarm Optimizers, PhD Thesis, *University of Pretoria*, 2001.

Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because of it is a peer reviewed international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per year by International Frequency Sensor Association (IFSA). In additional, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc. Since 2011 the journal is covered and indexed (including a Scopus, Embase, Engineering Village and Reaxys) in Elsevier products.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

- Physical, chemical and biosensors;
- Digital, frequency, period, duty-cycle, time interval, PWM, pulse number output sensors and transducers;
- Theory, principles, effects, design, standardization and modeling;
- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
- Signal processing;
- Frequency (period, duty-cycle)-to-digital converters, ADC;
- Technologies and materials;
- Nanosensors;
- Microsystems;
- Applications.

Submission of papers

Articles should be written in English. Authors are invited to submit by e-mail editor@sensorsportal.com 8-14 pages article (including abstract, illustrations (color or grayscale), photos and references) in both: MS Word (doc) and Acrobat (pdf) formats. Detailed preparation instructions, paper example and template of manuscript are available from the journal's webpage: http://www.sensorsportal.com/HTML/DIGEST/Submition.htm Authors must follow the instructions strictly when submitting their manuscripts.

Advertising Information

Advertising orders and enquires may be sent to sales@sensorsportal.com Please download also our media kit: http://www.sensorsportal.com/DOWNLOADS/Media_Kit_2012.pdf