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Control and Modeling of Wind Turbines Using Genetic Algorithms and Support Vector Machines for Regression

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ABSTRACT

In this work, a hybrid approach based on the Support Vector machines (SVM) and genetic algorithms (GA) is developed. The SVM are learning machines that can perform binary classification and real value function approximation (regression estimation) tasks. This tool of the artificial intelligence founded on the theory of the statistical learning was selected for its great capacity of training and generalization. Since its difficult to fund an explicit relation between such conditions and parameters, the SVM are used to approximate this relation, through their training from examples. To optimize the configuration of our approach, namely the structure which gives us the most precise result in terms of error of prediction, we used the genetic algorithms for the choice of hyper-parameters of the SVM.

Keywords: *Variable Speed wind Turbine, Sliding Mode Control, Genetic Algorithm, Support Vector Machines.*

1 INTRODUCTION

Wind energy is gaining increasing importance worldwide. The processes of industrialization and economic development require energy. Fuels are the main energy resource in the world and are at the center of the energy demands. Wind turbines using aerodynamic lift can be divided according to the orientation of the axis of rotation on the horizontal axis and vertical axis turbines. The horizontal axis or propeller-type approach currently dominates wind turbine applications. A horizontal axis wind turbine comprises a tower; a nacelle is mounted on top of the tower. The nacelle contains the generator, gearbox, and rotor. There are several mechanisms to signal the gondola to the wind direction or to move the nacelle of the wind in the case of high wind speeds. In small turbines, the rotor and nacelle are oriented into the wind with a tail vane. In larger turbines, the gondola with the rotor is electrically yawed out of the wind in or in response to a signal from avane. Horizontal axis wind turbines typically use a different number of blades, depending on the purpose of the wind turbine. Turbines with two sheets or three blades are generally used for power generation. The most common design of modern turbines is based on the horizontal shaft structure. This design of wind turbine towers is assembled as shown in **Figure 1**.

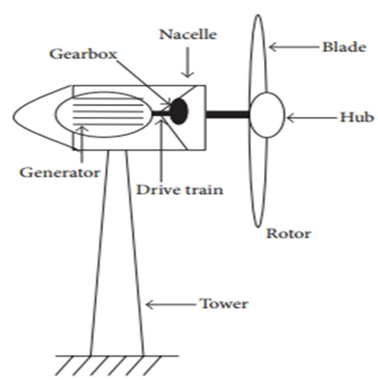

FIGURE 1: A horizontal axis wind turbine

The role of the tower is to raise the wind turbine above the ground to intercept the strongest winds to get more energy. Wind energy has evolved rapidly during the past three decades with increasing diameters of the rotor and the use of sophisticated power electronics to allow operation at rotor speed varies; see **Figure 2**.

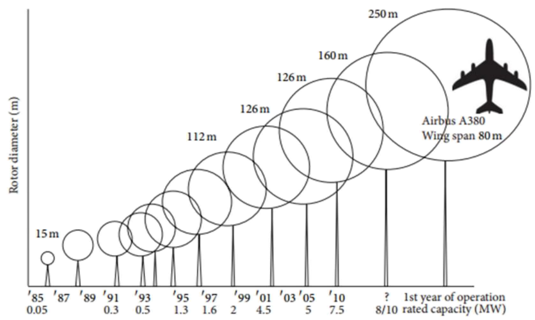

FIGURE 2: Evolution of the wind turbine dimensions.

2 WIND TURBINE STRUCTURE

The wind turbines can be classified based on their orientation and their axis of rotation, into horizontal axis wind turbines (HAWT) and vertical axis wind turbines (VAWT), which can be installed on the land or sea. The HAWT feature higher wind energy conversion efficiency due to the blade design and access to stronger wind, but they need a stronger tower to support the heavy weight if the nacelle and its installation cost is higher. The VAWT have the advantage of lower installation; however, their wind energy conversion efficiency is lower due to the weaker wind on the lower portion of the blades and limited aerodynamic performance of the blades. A comparison between the horizontal and vertical axis wind turbines is summarized in ***Table 1.***

Another form to classify the wind turbines is by speed control methods and power control methods. The wind energy conversion is divided into fixed and variable speeds. As the name suggests, fixed speed wind turbines (FSWT) rotate at almost a constant speed, which is determined by the gear ratio, grid frequency, and number of poles of the generator. The maximum conversion efficiency can be achieved only at a given wind speed, and the system efficiency degrades at other wind speeds. The wind turbine is protected by aerodynamic control of the blades from possible damage caused by high wind gusts. On the other hand, variable speed wind turbines (VSWT) can achieve maximum energy conversion efficiency over a wide range of wind speeds. The turbine can continuously adjust its rotational speed according to the wind speed. In doing so, the tip speed ratio which is the ratio of the blade tip speed to the wind speed can be kept at an optimal value to achieve the maximum power conversion efficiency at different wind speeds. A comparison between the fixed speed wind and variable speed turbines is summarized in ***Table 2***.

TABLE 1: Properties of HAWT over VAWT.

	Advantages
HAWT	(i) Higher wind energy conversion efficiency
	(ii) Access to stronger wind due to high tower
VAWT	(i) Lower installation cost and easier maintenance due to the ground level gearbox and generator
	(ii) Operation independent of wind direction
	Disadvantages
HAWT	(i) Higher installation cost, stronger tower to support heavy weight of nacelle
	(ii) The orientation is required
VAWT	(i) Lower wind energy conversion efficiency
	(ii) Higher torque fluctuations and prone to mechanical vibrations

TABLE 2: Advantages and disadvantages of FSWT and VSWT .

	Advantages
FSWT	(i) Simple, robust, reliable (ii) Low cost and maintenance
VSWT	(i) High energy conversion, efficiency (ii) Improved power quality (iii) Reduced mechanical stress
	Disadvantages
FSWT	(i) Relatively low energy conversion efficiency (ii) High mechanical stress (iii) High power fluctuations to the grid
VSWT	(i) Additional cost and losses due to use of converters (ii) More complex control system

3 Modeling of the Wind Turbine

Since vertical axis wind turbines have very low starting torque, as well as dynamic stability problems they are commonly found in small wind applications. On the other hand, horizontal axis wind turbines are the most common wind turbines and are most commonly used for wind farms, community wind projects, and small wind applications. In this paper, we only discuss the modeling and control methods of horizontal axis wind turbines.

3.1 Modeling Based on the Aerodynamic. The aerodynamic

The kinetic energy obtained by the blades of the wind is transformed into mechanical torque at the rotor shaft of the wind turbine; the model can be described of in spoiler (aeofrein); see ***Figure 7***.

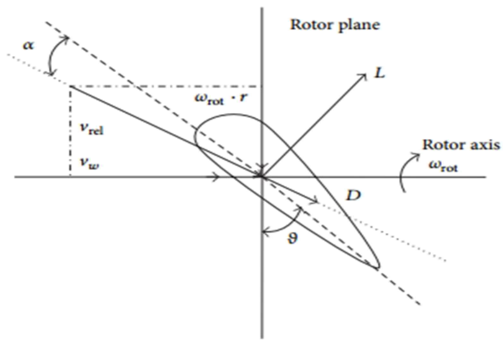

FIGURE 7: Aerodynamic model

The blades are attached to the rotor with the tip speed $\omega rot{\cdot}r$, where r is the length of the blade. The profile of the blade experiences a relative wind speed generated by overlapping the tip speed and wind speed vw. Wind is introduced from the lift profile (L) and drag forces (D) on the blade, resulting in the movement of these forces blade wind energy which is called the aerodynamic powerPw given as follows [1]:

$$P_w = \frac{1}{2}\rho_{\text{air}} \cdot A_r \cdot c_p(\lambda, \vartheta) \cdot \upsilon_w^3, \qquad (1)$$

Whereρair is the air density, vw is the free wind speed experienced by the rotor, A is the swept rotor area, and cp is the power coefficient. The power coefficient depends upon the pitch angle ϑ and the tip-speed-ratio:

$$\lambda = \frac{\omega_{\text{rot}} \cdot r}{\upsilon_w}. \qquad (2)$$

The power coefficient cp is typically given in a form of ***Figure 8***:

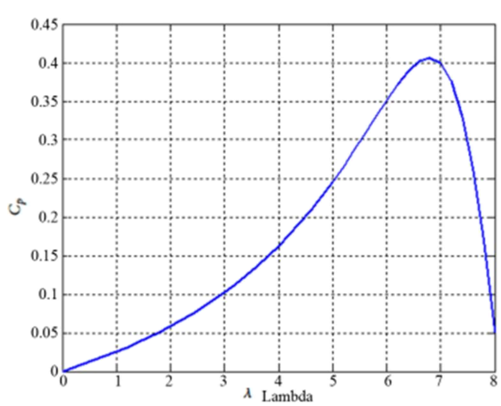

FIGURE 8: The power coefficient c_p versus the tip speed ratio

The torque on the rotor shaft (see ***Figure 9***), which is important for the axis model, can be calculated from the power with the aid of the rotational speed:

$$T_A = \frac{P_w}{\omega_r}, \qquad (3)$$

Where $\mathbf{wr}$ is the wind turbine speed (velocity of the rotor) and TA is the aerodynamic torque.

3.2 Modeling Based on the Mechanical Property. In the power

System analysis, the following four types of drive train models are usually used for the wind turbine available:

(i) six-mass drive train model
(ii) three-mass drive train model
(iii) two-mass shaft model
(iv) one-mass or lumped model

The simplified model of the power train is shown in ***Figure 9.***

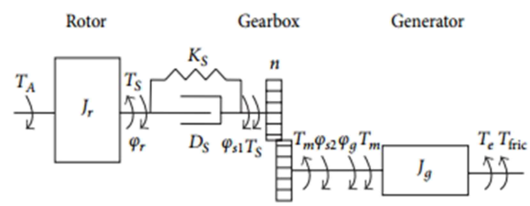

FIGURE 9: Drive train schematic for the modelling of a wind turbine

In this model, all masses are grouped into low and high speed shaft. This model is sufficient for transient stability analysis with a fixed speed. The inertia of the low speed shaft comes mainly from the rotating blades and the inertia of the high speed shaft. It is important to include all small masses of high speed shaft, since they have an important influence on the dynamic system due to the transformation of the transmission ratio. The stiffness and damping of the shaft are combined in equivalent stiffness and damping placed on the low speed side. The mass of the gearbox itself is insignificant and abandoned.

The input to the model for a two-mass system is defined as torqueTA, which is obtained by the aerodynamic system and the generator reaction torque Te. The output is the changes in the rotor speed ωr and generator speed ωg.

The dynamic of high speed generator can be expressed as a machine model. The differences in the mechanical drive torqueTm, the generator torque reaction Te, and torque losses due to friction $\mathbf{T fric}$, cause the change of angular velocity $\dot{\omega}_g$.

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$$T_m - T_e - T_{\text{fric}} = J_g \cdot \dot{\omega}_g,$$
$$\dot{\omega}_g = \ddot{\varphi}_g. \quad (4)$$

The change of the angular speed ωr is caused by the difference of the aerodynamic torque TA and shaft torque Ts at the low speed:

$$T_A - T_S = J_r \cdot \dot{\omega}_r,$$
$$\dot{\omega}_r = \ddot{\varphi}_r. \quad (5)$$

The mechanical driving torque Tm and shaft torque Ts are connected by the gear ratio:

$$T_m = \frac{T_s}{n}. \quad (6)$$

The dynamics of the shaft can be described by:

$$T_s = K_s \cdot \Delta\varphi + D_s \cdot \Delta\dot{\varphi},$$
$$\Delta\dot{\varphi} = \dot{\varphi}_r - \frac{\dot{\varphi}_g}{n} = \omega_r - \frac{\omega_g}{n}. \quad (7)$$

The final drive train dynamics is as follows:

$$\dot{\omega}_r = \frac{1}{J_r}\left(T_A - D_S \cdot \omega_r + \frac{D_s}{n}\omega_g - K_s \int \left(\omega_r - \frac{\omega_g}{n}\right) dt\right),$$
$$\dot{\omega}_g = \frac{1}{J_g}\left(-T_e - \left(D_g + \frac{D_s}{n^2}\right)\omega_g + \frac{D_s}{n}\omega_r - \frac{K_s}{n}\int \left(\omega_r - \frac{\omega_g}{n}\right) dt\right), \quad (8)$$

Where K is the stiffness constant and D is the damping constant of the shaft. To obtain the stiffness constant, the eigen frequency of the drive train has to be known. Consider a two-mass free swinging system; the eigen frequency is as follows:

$$\omega_{0S} = 2\pi f_{0S} = \sqrt{\frac{K_s}{J_{\text{ges}}}}. \quad (9)$$

Consequently, the stiffness constant of the low speed shaft is:

$$K_s = J_{\text{ges}} \cdot (2\pi f_{0S})^2. \quad (11)$$

The damping constant Ds can be calculated by:

$$D_s = 2\xi_s \cdot \sqrt{\frac{K_s \cdot J_{\text{ges}}}{\xi_s^2 + 4\pi^2}}, \quad (12)$$

Where ξ_s is the logarithmic decrement

4 CONTROL OF THE WIND TURBINE

There are many results on wind turbines control from the aerodynamic to generator energy. In this paper, we only discuss the horizontal axis wind turbine. This type of wind turbine is the most used in the market.

The performance of the wind turbine depends not only on hard ware, also on the wind turbine control technique.

The main control objectives of the wind turbine are as follows: Capture the wind power as possible as it can, maximize the wind harvested power in partial load zone, guarantee a certain level of resilience of the mechanical parts by alleviating the variable loads,

(i) Meet strict power quality standards (power factor, harmonics, flicker, etc.),

(ii) Transfer the electrical power to the grid at an imposed level in wide range of wind velocities.

The control system has three subsystems: aerodynamic control, variable speed control, and grid connection control; (see ***Figure 10***).

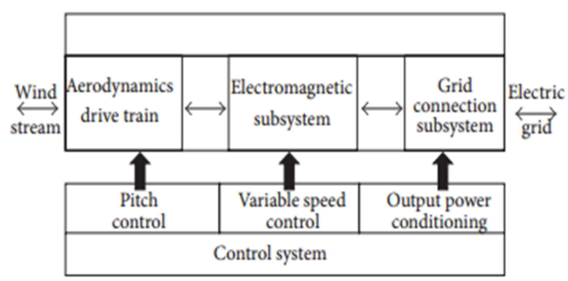


Figure 10: Main control subsystems of a wind turbine

In the following sections several popular control techniques will be discussed.

4.1 Aerodynamic Control

The wind turbine aerodynamics is very similar to the airplane. The blade rotates in the wind, because the air flowing along the surface moves faster than the up wind surface. This creates a lifting force to remove the sheet to rotate. The attack angle of the blade plays a critical role in determining the amount of force and torque generated by the turbine. Therefore, it is an effective means to control the amount of power. There are three methods to aerodynamically control for large wind turbines: passive stall, active stall, and pitch control.

(i) Passive stall control: the blade is fixed on the rotor hub in an optimum (nominal) attack angle.

When the wind speed is less than or equal to the nominal value, the turbine blades with the nominal attack angle capture the maximum possible power wind. With wind speed above the nominal value, the strong wind can cause turbulence on the surface of the blade, which faces away from the wind. As a result, the lifting force is reduced and eventually disappears with increasing wind speed by reducing the speed of rotation of the turbine. This phenomenon is called stall. The passive stall control does not need complex pitch mechanisms; however, the blades need a good aerodynamic design.

(ii) Active stall control: the stall phenomenon can be induced not only by higher wind speeds, but also by increasing the attack of the blade. Thus, active stall wind turbine shave blades with adjustable pitch control mechanism. When the wind speed exceeds the rated value, the blades are controlled towards the wind to reduce the captured power. Consequently, the captured power can remain at the nominal value by adjusting the blade angle of attack.

(iii) Pitch control: for the light and medium wind, the pitch control can optimize the operation of the wind turbine in the sense of maximizing rotor power. For the strong wind that exceeds the nominal level, pitch control maintains a desired operating condition. The optimization operation by the pitch control can increase rotor power up to 2%. This accuracy of the pitch angel is important but is not relevant for the stability investigations of short-term stress. Therefore, the steady-state angle of inclination can be adjusted to zero when the incoming wind is below the normal level. For strong wind, the steady-state angle is greater than zero and increases with increasing wind speed. Similar to the active stall control, the wind turbines with pitch control have adjustable blade in the rotor hub. When wind speed exceeds nominal value, the pitch controller reduces the attack angle, turning the blades (pitching) from wind gradually. The difference pressure in front and in the rear of the blade is reduced. The pitch control reacts faster than active stall control and provides better controllability.

4.2 Nonlinear Control. Sliding Mode Control

Sliding mode control is a robust nonlinear feedback control technique. It can be applied for the wind turbine control; see ***Figure 12.***

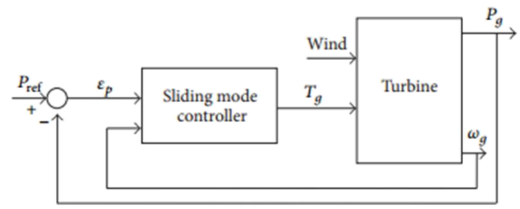


Figure 11. Sliding mode control for wind turbine

The tracking error εp is defined as $\varepsilon p = Pref - Pw$, where Pw is the aerodynamic power (rotor power) defined in (1) and (3) and $Pref$ is the reference power. The derivative of is:

$$\dot{\varepsilon}_p = \dot{P}_{\text{ref}} - T_A\dot{\omega}_r - \dot{T}_A\omega_r.$$

The dynamic sliding mode controller is defined as follows:

$$\dot{T}_A = \frac{(B+\lambda)}{\omega_r}\operatorname{sgn}\left(\varepsilon_p\right),$$

Where $\dot{B} = |\varepsilon_p|$, is the tip-speed-ratio defined in (2) and ωr is the wind turbine speed (velocity of the rotor) defined in (3):

$$\operatorname{sgn}(s) = \begin{cases} 1 & \text{if } s > 0, \\ -1 & \text{if } s < 0. \end{cases} \quad (25)$$

The closed-loop system is:

$$\dot{\varepsilon}_p = \dot{P}_{\text{ref}} - T_A\dot{\omega}_r - (B+\lambda)\operatorname{sgn}\left(\varepsilon_p\right). \quad (26)$$

The uncertainty is defined as $d = Pref - TA\ \omega r$, and it is bounded as $|d| < B1$; $B1$ is a positive constant. Then, (26) is rewritten as follows:

$$\dot{\varepsilon}_p = -(B+\lambda)\operatorname{sgn}\left(\varepsilon_p\right) + d. \quad (27)$$

A Lyapunov function is defined as follows:

$$V = \frac{1}{2}\varepsilon^2 + \frac{1}{2}(B - B_1)^2. \quad (28)$$

It is not difficult to see that its time derivative satisfies:

$$\dot{V} \le -\lambda\,|\varepsilon|\,. \quad (29)$$

By the LaSalle theorem, it is concluded that the tracking error converges asymptotically to zero. Since the sliding mode control system provides

dynamic invariant property with uncertainties, it has to increase gains when tracking error is not zero. The main problem of the sliding mode control is the chattering. To decrease this behavior the sign function can be approximated as **sgn(εp)≈ $\varepsilon p/(|\varepsilon p|+a0)$, a0** is small positive constant.
This prevents from increased mechanical stress due to strong torque variations.

4.3 Generalized Predictive Control. SVM Regression

The Libsvm program was used to build SVM models. This software is based on the function of classification. After some improvement, it can also be applied to the regression problem well. More introductions and implementations about Libsvm can be found in their website. The Libsvm regression was realized by the ε-Support Vector Regression (ε-SVR) with a radial basis function (RBF) kernel function. The ε-SVR algorithm is a generalization of the better known support vector classification algorithm to the regression case. Given **n** training vectors **xi** and a vector $y \in Rn$ such that, we want to find an estimate for the function **y= f(x)** which is optimal from a structural risk minimization viewpoint. According to **ε-SVR**, this estimate is:

$$f(x) = \sum_{i=1}^{n} (a_i^* - a_i) k(x_i, x_j) + b$$

Where **b** is a bias term and **k(xi,xj)** is a special function called the kernel. The coefficients **ai** and **ai*** are the solutions of the quadratic problem:

$$w(a,a^*) = -\varepsilon \sum_{i=1}^{n} (a_i^* + a_i) + \sum_{i=1}^{n} (a_i^* - a_i) y_i - \frac{1}{2} \sum_{i,j=1}^{n} (a_i^* - a_i)(a_j^* - a_j) k(x_i, x_j)$$

$$0 \le a_i, a_i^* \le C, \; i = 1, \dots, n, \qquad (30)$$

$$\sum_{i=1}^{n} (a_i^* - a_i) = 0$$

Parameters **C** and **ε** can be chosen by the user. The "penalty parameter" **C** may be as high as infinity, while usual values for ε are 0.1 or 000.1. The kernel function is used to convert the data into a higher-dimensional space in order to account for nonlinearities in the estimate function. A commonly used kernel is the Radial Basis Function (RBF) kernel:

$$k(x, y) = \exp(-\gamma \|x - y\|^2)$$

The parameter γ is selected by the user.
- The basic concept of the SVR is to map nonlinearly the original data x into a higher dimensional feature space. Hence, suppose we are given a training data set $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \subset N * R$ where **N** denotes the space of input patterns—for instance, Rk.

In ε—SVM Regression, the goal is to find a regression function f(x): that has at most ε deviation from the actually obtained targets **Yi** for all the training data. In other words, we do not care about error as long as they are less than ε, but will not accept any deviation larger than ε. An ε-insensitive loss function.

$$L_{\xi}(x, y, f(x)) = \begin{cases} | y - f(x) | - \varepsilon & if\, |y - f(x) \ge \varepsilon| \\ 0 & else \end{cases}$$

So the error is penalized only if it is outside the ε-tube. Fig.1 depicts this situation graphically. To make the SVM regression nonlinear, this could be achieved by simply mapping the training patterns xi by a nonlinear transform φ: N→F into some high dimensional feature space F. A simple example of the nonlinear transform φ is the polynomial transform function:

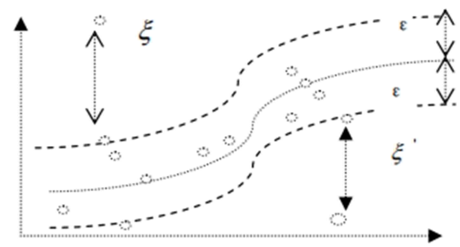


FIGURE 12: The epsilon insensitive loss setting corresponds for a linear Support Vector regression machine

A best fitting function:

$$f(x) = \sum_{i=1}^{N} w_i \varphi_i(x) + b = w^T \varphi(x) + b$$

Where $\varphi_i(x)$ is the feature of inputs x; both **Wi** and bare coefficients which are estimated by minimizing the regularized risk function: To avoid over-fitting in the very high-dimension feature space, one should add a capacity control term, which in the SVM case results to be $\|w\|^2$. Formally, the SVM regression model can be written as a convex optimization problem by requiring:

$$\varepsilon - tubeMinimize: R(w, \zeta, \zeta^*) = \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{n} (\zeta_i + \zeta_i^*)\right)$$

With the constraints:

$$w_i \phi(x_i) + b - d_i \le \varepsilon + \zeta_i^*, i = 1, 2, \dots, N,$$

$$-w_i \phi(x_i) - b + d_i \le \varepsilon + \zeta_i, i = 1, 2, \dots, N,$$

$$\zeta_i, \zeta_i^* \ge 0, i = 1, 2, \dots, N$$

The constant C>0 determines the trade off between the complexity of f(x) and the amount up to which deviations larger than ε are tolerated. We can estimate a linear function in the feature space that makes SVM regression attractive. In addition, the regression task was achieved by solving a convex programming with linear constraints that means it has a unique solution. The size of insensitive ε— is a pre-defined constant. The modeling performance may seriously affected by the selection of a parameter. The insensitive ε— zone represented as a tube shape in the SVM regression, only the training data outside the ε — tube will be penalized. In many real-world applications, the effects of the training points are different. We would require that the precise training points must be regressed correctly, and would allow more errors on imprecise training points.

The constrained optimization problem in **(30)** is solved using the following primal Lagrangian form:

$$Min \quad f = MAPE_{cross \quad validation} = \frac{\sum_{i=1}^{l} |a_i - p_i|}{l} \quad *100\%$$

Karush-Kuhn-Tucker (KKT) conditions are applied to the regression and (4) thus yields the dual Lagrangian,

$$J(a_i, a_i^*) = \sum_{i=1}^{N} d_i(a_i - a_i^*) - \varepsilon \sum_{i=1}^{N} (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \quad (a_j - a_j^*) K(x, x_i)$$

s.t.

$$\sum_{i=1}^{N} (a_i - a_i^*) = 0, \quad 0 \le a_i, a_i^* \le C, \quad i = 1, 2, ..., N.$$

Both αi and α i* are called Lagrangian multipliers that satisfy the equalities $\alpha_i \cdot \alpha_i^* = 0$.

Hence an optimal desired weights vector of the regression hyper-plane is represented as

$$w^* = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x_i, x_j)$$

Here, **K(xi,xj)** is called the kernel function. The value of the kernel equals the inner product of two vectors **xi** and **xj** in the feature **ϕ(xi)** and ϕ(xj);

that is $K(x_i, x_j) = \varphi(x_i) \;*\; \varphi(x_j)$

Any function that satisfies Mercer's Condition by Vapink can be called the Kernel function.

There are several frequently-used kernel functions; all of them have their own advantages and disadvantages.

The selection of the three parameters **(c, σ, ε)** of a SVM model is important to the accuracy of forecasting.

Notably, there are only two parameters, **ε** and **c**, for the linear SVM model. However, structural methods for confirming efficiently the selection of parameters efficiently are lacking. Therefore, AG is used in the proposed SVM model to optimize parameter selection.

4.4 Intelligent Control. Algorithm Genetic

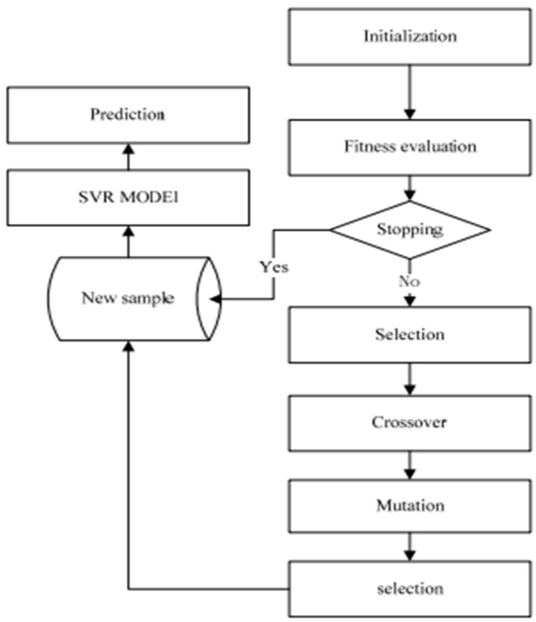
The objective is that the controller will allow the plant to produce the desired result. To accomplish this, the intelligent controller must be trained so that the input error $\varepsilon p = (t) = P\mathrm{ref} - Pw = (t) - xn(t)$ produces the proper control parameter $TA = u(t)$ to be applied to the plant to produce the aerodynamic power $Pw = xn(t)$.

Genetic algorithm (GA), proposed by Holland, which is an organized random search technique and which imitates the biological evolution process. The algorithms try to retain genetic information form generation to generation that are based on the principle of the survival of the fittest. GA has been successfully applied to a series of problems such as data mining and optimization. It has also been used for the feature selection in SVM modeling.

As to a specific problem, The GA looks a solution as an individual chromosome. It defines an initial population of these individuals, which represent the solution space of the problem. First a set of chromosomes is randomly chosen from the search space to form the initial population. Second the individuals are selected in a competitive manner, based on their fitness as measured by a specific objective function. The chromosome are binary-encoded, each bit of the chromosome represents a gene.

The Genetic algorithm for the feature selection is presented as follows.

Step 1: Initialization of the population.
Step 2: Fitness evaluation of each chromosome.
Step 3: Selection of chromosomes from the current population.
Step 4: Crossover.
The newly created chromosomes constituted a new population.
Step 5: Mutation: The mutation operation follows the crossover operation and determines whether a chromosome should be mutated in the next generation.
Step 6: Elitist strategy: The fitness value was calculated for the chromosomes of the new population. If the minimum fitness value of the new population is smaller than that of the old population, then the old chromosome can be replaced with the new chromosome of the minimum fitness value.
Step 7: Stopping criteria.



5 CONCLUSION

Green energy has opened an important branch and shows in the rise of technology. The wind turbines and related techniques, environment, structure, and control methodology, are paid more attention recently.

This paper presents the most common used wind turbine models which are classified with respect to different objectives as are more production energy, safety of turbine, connection to grid; consequently, the wind turbine dimensions are increased and the control methods are required to respond quickly and effectively to the important task of the power generation.

The motivation of this study is based on the evidence that different forecasting models can complement each other in approximation data sets. This paper applied SVM model composed of linear and nonlinear SVR to the forecasting field of financial returns. Then Genetic algorithm is used for the feature selection in SVR modeling to search for better combinations three parameters in SVM. The algorithm still has to be improved; other advanced searching techniques to determine the suitable parameters should be combined with the SVR model.

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