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Particle Swarm Optimization based predictive control of Proton Exchange Membrane Fuel Cell (PEMFC)*

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Abstract: Proton Exchange Membrane Fuel Cells (PEMFCs) are the main focus of their current development as power sources because they are capable of higher power density and faster start-up than other fuel cells. The humidification system and output performance of PEMFC stack are briefly analyzed. Predictive control of PEMFC based on Support Vector Regression Machine (SVRM) is presented and the SVRM is constructed. The processing plant is modelled on SVRM and the predictive control law is obtained by using Particle Swarm Optimization (PSO). The simulation and the results showed that the SVRM and the PSO receding optimization applied to the PEMFC predictive control yielded good performance.

Key words: Support Vector Regression Machine (SVRM), Proton Exchange Membrane Fuel Cell (PEMFC), Particle Swarm Optimization (PSO), Predictive control

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INTRODUCTION

Fuel cells have attracted more attention in the last few years due to scarcity of the world energy source. The Proton Exchange Membrane Fuel Cell (PEMFC) is the focus of current development efforts because it is capable of higher power density and faster start-up than other fuel cells (Zhang *et al.*, 2004). Research emphasis is on high power density with adequate energy conversion efficiency. PEMFC performance is related to many factors, among which electrolyte membrane humidity is very important. The membrane requires adequate humidification for proper performance (Rowe and Li, 2001). But when for a fuel cell product which structure, the character of the electrolyte membrane and the catalyzer content could not be changed, we can improve the PEMFC power by adjusting the electrolyte membrane humidity (Li *et al.*, 2004; Sridhar *et al.*, 2001). To maintain high fuel cell efficiency requires, a predictive control system for the output power is necessary for maintaining optimal temperature, membrane humidity and pressure of reactants across the membrane. We use the Support Vector Regression Machine (SVRM) to build a predictive model for the output power prediction control system of PEMFC. SVRM is an important part of Statistical Learning Theory, and has good potential for modelling time-sequence events (Müller *et al.*, 1999). Because of its distinct advantage in modelling of nonlinear system, SVRM has become a new strong tool in the intelligent control field in recent years. Supported by mathematical theory, SVRM nonlinear modelling and SVRM nonlinear control theory is a new control theory suitable for complex nonlinear system. Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart (1995), who were inspired by the social behavior of birds in a flocking and fish in a school. PSO uses local processes to learn from the unpredictable group dynamics of social behavior, applies it to solve optimization

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problems, as an evolutionary computation technique, is easy to implement and has few parameters to adjust. In view of the above virtues, we apply PSO algorithm to the receding optimization of PEMFC predictive control.

The remainder of this paper is organized as follows: Section 2 describes the basic principle of SVRM and SVRM predictive control. Section 3 focuses on the mathematical modelling of PEMFC. The Particle Swarm Optimization algorithm for receding optimization and PSO based predictive control of PEMFC are described in Section 4. The last section gives the conclusion and direction of future works.

PRINCIPLES OF SUPPORT VECTOR MACHINES REGRESSION (SVMR) AND SVRM PREDICTIVE CONTROL

Principles of Support Vector Machines Regression (SVMR)

SVMR's basic idea is to map the data x into a high dimensional feature space F via nonlinear ϕ mapping and to do linear regression in this feature space (Müller *et al.*, 1999).

$$f(x)=(\boldsymbol{\omega}\cdot\phi(x))+b, \tag{1}$$

with $\phi:\mathbb{R}^n\rightarrow F$, $\boldsymbol{\omega}\in F$, where b is threshold.

Then the nonlinear regression in low dimensional input space $\mathbb{R}^n$ can be mapped into the high dimensional feature space F where linear regression is performed. We may determine $\boldsymbol{\omega}$ from the data by minimizing the sum of the empirical risk functional $R_{\mathrm{emp}}[f]$ and a complexity term $\|\boldsymbol{\omega}\|^2$ since ϕ is fixed (Müller *et al.*, 1999). So we may find function f that minimizes the risk functional:

$$R_{\mathrm{reg}}[f]=R_{\mathrm{emp}}[f]+\lambda\|\boldsymbol{\omega}\|^2=\sum_{i=1}^{l}C(f(x_i)-y_i)+\lambda\|\boldsymbol{\omega}\|^2, \tag{2}$$

where l denotes the sample size, $C(\cdot)$ is a cost function determining how we penalize estimation errors and λ is a regularization constant.

The vector $\boldsymbol{\omega}$ can be written in terms of the data points

$$\boldsymbol{\omega}=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)\phi(x_i) \tag{3}$$

with α_i, α_i^* being the solution of the $R_{\mathrm{reg}}[f]$.

Considering Eqs.(1) and (3), we may get the regression function in the low dimensional input space.

$$\begin{aligned} f(x)&=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)(\phi(x_i)\cdot\phi(x))+b \\ &=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)k(x_i,x)+b, \end{aligned} \tag{4}$$

$k(x_i,x)=(\phi(x_i)\cdot\phi(x))$ is kernel function.

The kernel approach is employed to address the problem of dimensionality.

SVRM predictive control

For a single input single output nonlinear model (Wang and Wang, 2004):

$$\begin{aligned} &y(k+1)=f(y(k),\ldots,y(k-n),u(k),\ldots,u(k-m)),\\ &y\in\mathbb{R},u\in\mathbb{R},m\le n. \end{aligned} \tag{5}$$

where u is the input control variable of the system, y is the output variable of the system.

Given the continuous controlled input: $u(k-m)$, $u(k-m+1)$, …, $u(k)$. The system output: $y(k-n)$, $y(k-n+1)$, …, $y(k)$. If we let:

$$\boldsymbol{U}(i)=(y(i), y(i-1),\ldots, y(i-n), u(i), u(i-1), \ldots, u(i-m)), \tag{6}$$

where i=1, 2, 3, …, n. Then the corresponding predictive control is:

$$y(k+1)=f(\boldsymbol{U}(i)). \tag{7}$$

So the training samples: $(\boldsymbol{U}(i), y(i+1))$, i=1, 2, 3, …, n.

We may get the linear output shown as follows by using SVRM to map the dataset to high dimensional space.

$$\hat{y}(k+1)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(\boldsymbol{U}(i),U(k))+b, \tag{8}$$

where $\boldsymbol{U}(i)$ are the support vectors.

The model can be trained online or off-line. The SVRM model can be modified online.

MATHEMATICAL MODELLING OF PEMFC

The reason for choosing a PEMFC lies in its easy and safe operational modes, low temperature gradient, low chance of catalyst poisoning and wide scope of application in power distribution systems (Freire and Gonzalez, 2001). Various attempts were made to model fuel cell systems. Most processes in industry when considering small changes around an operating point, can be described by a linear model of very high order (Camacha and Bordon, 1999). Since the performance of the PEMFC is dependent more on hydrogen humidification than on oxygen humidification (Sridhar *et al*., 2001), our work in this paper is restricted to the humidification of hydrogen using Nafion® membrane. When the flow rate of hydrogen, area and membrane type are constant for a given PEMFC, we may change the relative humidification of hydrogen to improve the performance of the fuel cell (Sridhar *et al*., 2001). The relationship between fuel cell power output and hydrogen humidification can be simplified as a first-order plus dead-delay (Camachao and Bordon, 1999; Li *et al*., 2004).

The transfer function of this model is:

$$G(s)=\frac{K}{1+\tau s}\mathrm{e}^{-s^{\tau_\mathrm{d}}},$$

where K is the steady state gain of the system, τ is time constant, τ_d is the dead time. The input variable is the relative humidification of hydrogen. Output variable is the output power of the fuel cell. Based on data in (Sridhar *et al*., 2001) and using the reaction curve method, we obtained the process parameters: K=32, τ=20, τ_d=4. Fig.1 shows the step response of the process.

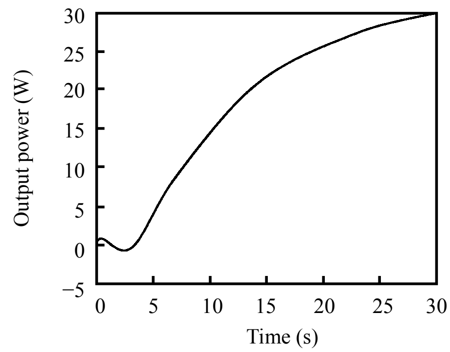

Fig.1 Reaction curve of the process

PARTICLE SWARM OPTIMIZATION BASED PREDICTIVE CONTROL OF PEMFC

PSO algorithm

PSO is initialized with a group of random solutions (called swarms). Each potential solutions, called particles, fly through the problem space at velocities following those of the current optimum particles and searches for optima by updating generations (Shi and Eberhart, 1999). In every iteration, each particle is updated by following two "best" values. The first one is the best solution (*fitness*) achieved so far (fitness value is also stored). This value is called *pbest*. Another "best" value tracked by the particle swarm optimizer is the best value obtained so far by any particle in the population. When this best value is a global best, it is called *gbest*. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called *lbest* (Shi and Eberhart, 1999). After finding the two best values, the particle updates its velocity and positions with the following equations:

$$v[]=w\times v[]+c1\times rand()(pbest[]-present[]) +c2\times rand()(gbest[]-present[]), \tag{9}$$

$$present[]=present[]+v[], \tag{10}$$

where v[] is the particle velocity, w is inertia weight. It regulates the trade-off between the global exploration and local exploitation abilities of the swam. *present*[] is the current particle (solution). *pbest*[] and *gbest*[] are defined as stated before. *rand*() is a random number between (0,1). $c1$, $c2$ are learning factors.

The inertia weight is set to the following equation (Shi and Eberhart, 1999):

$$w=w_{\max}-((w_{\max}-w_{\min})/iter_{\max})\times iter, \tag{11}$$

where $w_{\max}$ is the initial value of weighting coefficient; $w_{\min}$ is the final value of weighting coefficient; $iter_{\max}$ is the maximum number of iterations or generation; *iter* is the current iteration or generation number.

PSO algorithm for receding optimization in predictive control

The receding optimization objective function of the predictive control is shown as follows (Onnen *et al*., 1997):

$$\min J=\sum_{i=1}^{p}[r(k+i)-\hat{y}(k+i)]^2, \tag{12}$$

where p is the predictive horizon, $\hat{y}(k+i)$ is predicted output values, $r(k+i)$ is the reference. k is present time. The equation accounts for the minimizing of the variance of the process output from the reference.

PSO was used in 1999 as an optimization technique to control process (Yoshida, 1999). Xiao (2004) proposed PSO for neural network predictive control and used adaptive PSO for the receding optimization of the RBF neural network predictive control. One of the advantages of PSO is that it takes real numbers as particles. It is not like GA, which needs to change to binary encoding, or special genetic operators have to be used. So we can directly set the predicted output values as particles while the reference is the pre-determined setpoints. The fitness function is the optimization objective function J. When the predictive horizon p is chosen as 100, the swarm size is set to 50, maximum iteration number is set to 1000.

The flow chart of the PSO algorithm for predictive control is shown in Fig.2.

We simulate the receding optimization of the objective function. PSO learning factors $c1=c2=2$, $w_{max}=0.95$, $w_{min}=0.4$, $iter_{max}=1000$.

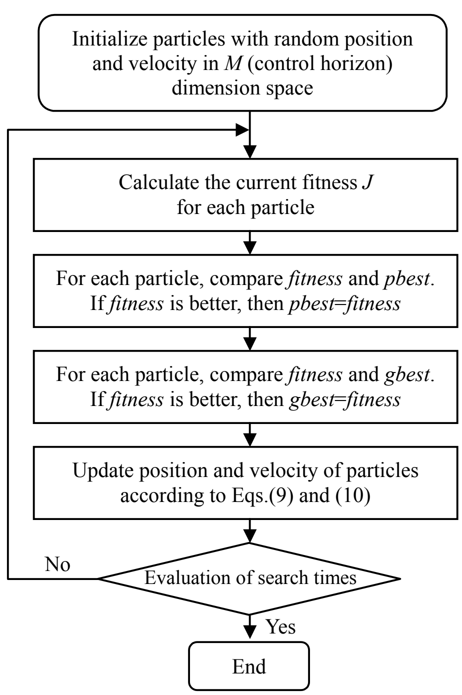

Fig.2 Flow chart of PSO for predictive control

The simulation process of PSO searching dynamics for PEMFC optimization is shown in Fig.3 showing the generations of the populations during the PSO dynamic optimization process.

The axes show: x=*gbest*(1); y=*gbest*(2); z=*gbest*(2); *gbest* expresses the global best obtained by any particle in the population shown in Eq.(9).

PSO based predictive control of PEMFC

We conducted simulation of the PEMFC, and the process plant is described in Section 3. Based on experiments, SVRM parameters are set as follows: based on the Lagrangian multipliers C is set to 10. Kernel function is chosen as Gaussian standard deviation. The cost function adopted linear ε insensitive cost, and ε is set to 0.1. PSO learning factors $c1=c2=2$, while the other parameters can be chosen as described

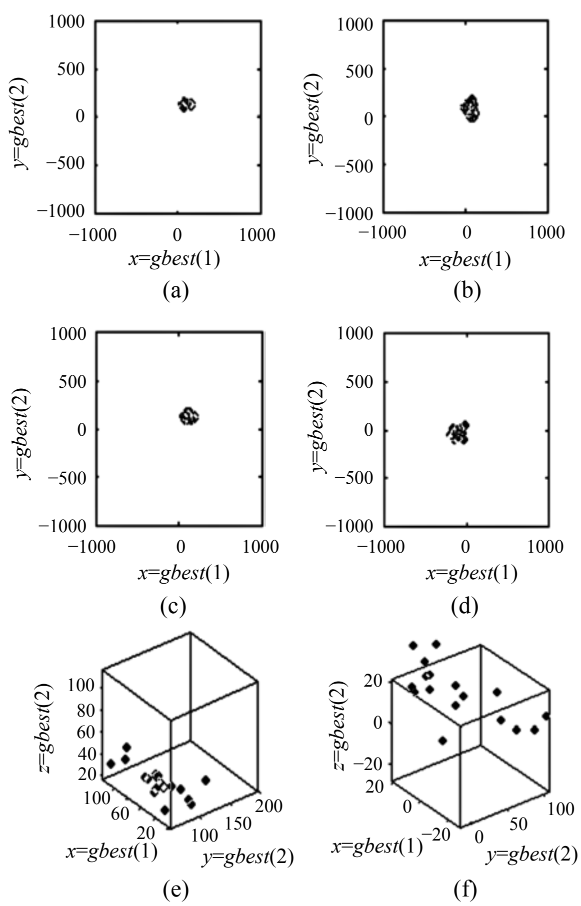

Fig.3 Search dynamic for PEMFC optimization ($c1=c2=2$, $w_{max}=0.95$, $w_{min}=0.4$). (a) Generation 1; (b) Generation 2; (c) Generation 10; (d) Generation 50; (e) Generation 100; (f) Generation 200

in the above section.

The output regression and predictive result for the random input can be seen in Fig.4.

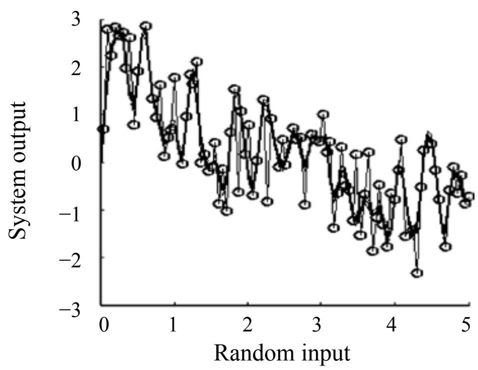

Fig.4 Output regression based on SVRM and PSO receding optimization

The grey curve in Fig.4 is the original output curve of the first 100 steps in for the random input signal, the black curve shows the predictive output of the system. The circles show the SVRM regression result of the input-output data.

Fig.4 shows that the regression curve is very near to the original data, indicating that the regression result is good. The predictive curve obtained by using the Gaussian standard deviation kernel function differs little from the actual value and so, has predictive ability.

CONCLUSION AND FUTURE WORK

This paper introduced a PSO based predictive control of PEMFC output power. The processing plant is modelled on SVRM and the receding optimization adopted PSO algorithm. SVRM is a modelling approach based on structural risk minimization principles. We may get more accurate model for PEMFC with small samples by using the SVRM modelling approach. PSO optimization requires only simple mathematical operators. This algorithm is simple to implement and effective, and is inexpensive in terms of memory and time required. This approach provides solutions with better quality within a reasonable time limit. The results of the experiment showed that the presented algorithms are effective. The presented predictive control based on SVMR and PSO algorithm for receding optimization resolved the delay of the PEMFC and reduced the complexity of the receding optimization algorithms. We may make the output power of the PEMFC change with the set point and improve the output performance by adjusting the relative humidification of hydrogen. Thus this predictive control algorithm is very important for fuel cell optimization management. We will construct more accurate mathematical model and combine other optimization methods to get the most optimization predictive control signal series, and design the online SVM identification to achieve online real-time predictive control of PEMFC output power.

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