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Neuro-fuzzy based Forecast Engine for Electric Load Prediction

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ABSTRACT：The Electric load series always presents complex phenomenon because of the influence of many complicated facts, various forecasting results can be obtained by using different models for a given electric power utility. In this paper, a novel approach that integrated fuzzy rule based systems for day-ahead price forecasting was developed. In this model the input of price data is clustered by TS fuzzy model. Also, to solve the objective function, a newly developed meta-heuristic algorithm of improved particle swarm optimization (IPSO) has been employed. The proposed method has been examined and tested on a practical system. The test results show that the improved PSO has better convergence and faster calculation speed than the basic PSO, and the presented combination forecast model has improved the accuracy.
KEY WORDS：Load forecasting, Particle Swarm Optimization, NN, Fuzzy mechanism

1. Introduction

The forecasting of electric load has always been important for the secure and economically beneficial operation of a power system. The short-term load forecasting has attracted many scholars' interests in the modeling theory of forecasting for a long time. Some effective achievements have been harvested [1]-[5]. But The electric load series always presents complex phenomenon because of the influence of many complicated facts, various forecasting results can be obtained by using different models for a given electric power utility. Some specialists think that individual models work well in some certain electricity grids or areas over a certain period of time, but are not suitable under other conditions. The reason is that a basic forecasting model is only a certain kind of mathematical algorithm that tries to imitate load change rules but does not work very well in every possible condition [6]. Some optimal technologies have been used to solve the combination forecasting model weight optimization problem, including the algorithm based on Least-square technique, genetic algorithms-GAs, evolutionary programming-EP and etc [7]-[9]. Particularly, with its sound exploration ability both global and local, a new evolution technology, named particle swarm optimization, has become the new focus of research [10]-[13]. The achievements encourage people to make further research in this field. The paper introduces an improved Particle swarm optimization for electric load combination forecasting model weight optimization. The new method applies a self-adaptive weight scale operator to avoid being trapped in the local optimum in conventional Particle swarm optimization. The proposed method has been examined and tested on a practical system. The test results show that the improved PSO has better convergence and faster calculation speed than the basic PSO, and the presented combination forecast model has improved the accuracy.

2. Neuro-Fuzzy Forecast Engine

2.1. Straitjacket Neural System

The aim of Straitjacket system is to provide an unsupervised learning device which assembles the Cartesian product of Fuzzy System necessary for estimation. Straitjacket is a heuristics without optimization criteria similar to Kohonen's algorithm, but we applied some important modifications in topology and activation to ease convergency and termination problems described at critics of Kohonen's system.

Topology: Straitjacket neural network has input and output neuron fields as presented in Fig. 1.

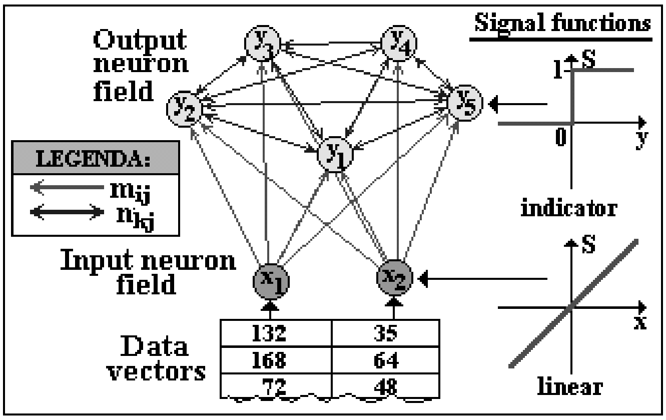

Figure 1 Topology of Straitjacket neural network

- Number of real valued input neurons equals number of decision variables. Observation vectors of the sample database are cyclically loaded to input field, which transfers values without any change toward output field through full feedforward connection.

- Binary valued output neurons have indicator signal function. Their membrane value signs active or inactive state. Besides binary membrane value every output neuron has a real agglomerative weight. Interconnection synaptic vectors of output neurons are space_coordinates in the decision space. Output neurons are full connected each other with bi-directional, competitive intraconnection synapses. Geometrically, we can see output field as set of coordinate points in decision space and a non-directed graph with weighted edges connecting them. We call the graph Straitjacket-web, because it will stretch on coordinate points as a straitjacket during iteration.

Activation and learning: The aim of the learning is to organize Straitjacket-web as space grid_model, 'skeleton' of the hypersurface of the unknown density function in the decision space. Straitjacket's learning is a composition of a Feature Mapping and a very simple hierarchical clustering named Competitive Actor Termination (CAT). The two components are in complemented connection, but they complete fairly different objectives:

1. Feature mapper changes space coordinates of output neurons by their actual Straitjacket_web weights. We applied the following differences from Kohonen Feature Mapper to reach better convergency:

- Output neurons are posed on data points at the initialization to reduce the length of trajectories, on which output neurons have to run toward cluster centers.

- There are no winner selection among output neurons as it happens in Kohonen-system. Every active output neurons are paired with observations and modify their space coordinates in one period. This parallel processing means independence from the sequence of data, but requires more computations.

- We applied full connected, non-directed graph as space grid instead of 1, 2 or 3 dimensional grid with deforming hypercubic cells used by Kohonen. This way, we can avoid most of the difficulties connected with dimension number of the web detailed at the second part.

- As we don't have hypercubic cells, we cannot use Kohonen's neighborhood formula to calibrate Straitjacket-web weights. But the basic principle is the same as Kohonen's: connection with closer neighbor gets higher weight. Neighbor-connections of an output neuron are competing with neighbor-distances to get higher web-weight. Web weights are calibrated with the help of neighborhood characteristics resulted multiplying inversed Neighbor-Distance Distribution Profiles (NDDPs) of the referring output neurons.

On the horizontal axis are the distance resolution intervals, on the vertical axis are distance weights. Dotted curves are NDDPs of two given output neurons. Solid curve is the neighbourhood characteristics of the connection between the two output neurons created by multiplying NDDPs.

2. CAT changes web weights of output neurons by their actual space coordinates and distance._The aim is to reduce number of active output neurons and provide simple termination condition. CAT inactivates the lower agglomerative weighted output neuron when two output neurons' Euclidean distance in the decision space is under the actual CAT-distance. When number of active neurons is equal or smaller than the predefined number of requested cluster centroids, the iteration stops.

Describing Straitjacket algorithm, we use the following symbols:

Indexes:

$i=1..n$ - index and number of the variables and input neurons

$i = 1..s,\ 0 < s < n$ - index and number of the input variables

z_i $i = 1..n$ - decision variables

$f, f' = 1..g$ -indexes and number of observations

$j, k = 1..m$ - indexes and number of output neurons, **$g \geq m \geq$** □

$l=1..o$ - index and number of the distance resolution intervals

Inputs and parameters:

$D_{f\times n}=(\underline{d}^T_1,..\underline{d}^T_g)$ -sample database matrix, data vectors, **$\underline{d}^T_f \in T \subset R^n$ $f=1..g$** Euclidean decision space

$\underline{e} = (e_1,..e_s)$ - actual input vector of estimation

□□$\in$ **[0,1]** - Straitjacket-web stretching force (0 - very strong, 1 - weak)

□□□□□□□□m - number of the requested cluster centroids

Other symbols:

$\underline{w}(t)=(w_1(t),..w_m(t))$ - agglomerative weights of output neurons in the **t**-th iteration step

$\underline{x}(t)=(x_1(t),..x_n(t))$ - input neuron field membrane vector in the **t**-th iteration step

$\underline{y}(t)=(y_1(t),..y_m(t))$ - output neuron field membrane vector in the **t**-th iteration step

$M_{n\times m}(t)=(\underline{m}^T_1(t),..\underline{m}^T_m(t))$ - interconnection synaptic matrix between input and output neuron fields in the **t**-th iteration step

$\underline{m}^T_j(t)$ - interconnection synaptic vector of the **j-**th output neuron in the t-th iteration step

$d(\underline{m}^T_j(t),\underline{m}^T_k(t))$ - Euclidean distance of 2 vectors

$N_{m\times m}(t))=(\underline{n}^T_1(t),..\underline{n}^T_m(t))$ - symmetric intraconnection synaptic matrix of output neuron field in the **t**-th iteration (Straitjacket-web weights)

$P_{m\times o}=(\underline{p}_1,..\underline{p}_m)$ - matrix of inversed neighbor distance distribution profiles (NDDPs) of output neurons

$\underline{v}=(v_1,..v_o)$ - vector of distance resolution intervals

STEP 1 Initialization

1.1. Init matrices

Normalize **D** and **$\underline{e}$** into **$[0,1]^n$** unit hipercube by minimum to maximum range of every variables. Init iteration period counter: **t:=0**

Pose interconnection synaptic vectors of output neurons on the first **m** data vector:

$$\underline{m}^T_j(0):=\underline{d}^T_j \quad j=1..m$$

Set every output neuron to active state:

$\mathbf{y_j(t):=1 \quad j=1..m}$

Initialize agglomerative weights:

$\mathbf{w_j(t):=1 \quad j=1..m}$

Determinate distance resolution intervals:

$\mathbf{v_l:=l/o \qquad l=1..o}$

Init upper database vector loading counter: **f:=m**

1.2. Calibrate Straitjacket-web

Aggregating agglomerative weights of output neurons:

$$q(t) := \sum_{j=1}^{m} \left(w_j(t) \times y_j \right)$$

Calculate NDDPs of output neurons:

$$p_{jl} := \frac{q(t) - \sum_{k=1}^{m} \left(w_k(t) \middle| d\left(\underline{m}_j^T(t), \underline{m}_k^T(t) \right) < v_l \right)}{q(t)}$$

$\mathbf{j=1..m \mid y_j(t)=1, l=1..o}$

Determinate Stratjacket-web weights:

$\mathbf{n_{jk}:=p_{jr}\times p_{kr} \quad j=1..m, k=1..m}$

where:

$\mathbf{r \mid v_r < d(\underline{m}^T{}_j(t),\underline{m}^T{}_k(t)) \leq v_{r+1}}$

STEP 2 Iteration cycle

2.1. Feature Mapping

Loading data vectors cyclically to input membrane vector and calculate new space coordinates of output neurons:

$\mathbf{\underline{x}(t):=\underline{d}^T{}_k}$

$$\underline{m}_j^T(t+1) := \begin{cases} n_{jk} \times \left[\underline{x}(t) - \underline{m}_j^T(t) \right] + \underline{m}_j^T(t) & if \quad j \neq k \\ \alpha \times \left[\underline{x}(t) - \underline{m}_j^T(t) \right] + \underline{m}_j^T(t) & if \quad j = k \end{cases}$$

j= 1..m | yj(t) = 1, k = 1..m

2.2. Competitive Actor Termination

$$\min dist(t) = \underset{j=2}{\overset{m}{MIN}} \left(\underset{k=1}{\overset{j-1}{MIN}} \left(d\left(\underline{m}_j^T(t+1), \underline{m}_k^T(t+1) \right) \right) \right)$$

IF $\mathbf{d(\underline{m}^T{}_j(t+1),\underline{m}^T{}_k(t+1)) = mindist(t)}$ THEN BEGIN

Determining indexes of survivor (**a**) and looser (**b**) neurons:

$$a := \begin{cases} j & if \quad w_j(t) > w_k(t) \\ k & else \end{cases} \qquad \textbf{(3.12)} \qquad b := \begin{cases} k & if \quad w_j(t) > w_k(t) \\ j & else \end{cases}$$

Modify Straitjacket-web weights of the survivor neuron:

$$n_{au}(t+1) := \frac{n_{au}(t) \times w_a(t) + n_{bu}(t) \times w_b(t)}{w_a(t) + w_b(t)}$$

$u = 1..m \mid y_u(t)=1,\ u \neq j,\ u \neq k$

$n_{jk}(t+1) := w_b(t)/w_a(t)$

Aggregate agglomerative weights to survivor and inactivate looser:

$w_a(t+1) := w_a(t) + w_b(t)$

$y_b(t+1) := 0$

END;

$k = 2..m \mid y_k(t)=1,\ j = 1..k-1 \mid y_j(t)=1$

2.3. Load new data vector from upper part of database

If we order output neuron to every single observation of the sample database - as it happens at Kosko's DCL-AVQ algorithm - increasing number of observations will increase computational requirement on the third power, memory requirement on the second power, making our approach awkward to treat larger databases. Therefore, we share sample database two parts:

- Lower database - observations indexed **f = 1..m** - are directly loaded to intraconnection synaptic matrix **M** at initialization and treated parallel way.

- When CAT inactivates the **k**-th output neuron, we load the next data vector from upper database (**f = m+1..g**) to the **k**-th data- and intraconnection synaptic vectors and recompute the corresponding row of matrices **N** and **P**, activating **k**-th output neuron again. With the help of this 'lifecycle' of output neurons, we can treat larger sample databases. We give up the concept of full parallel treatment at higher database, so results will depend on the sequence of upper database samples. But computational and memory requirement increases linearly by number of variables and number of observations also. Naturally, we extend size of low database (**m)** as big as available memory and CPU time allows. The upper-lower database method is particularly useful when we have smaller starting database and some new samples in every time period.

IF **g > f** THEN BEGIN

Load new data vector from upper part of database:

$f := f+1,\ \underline{d}^T_k := \underline{d}^T_f,\ w_k(t+1) := 1$

Activate **j**-th output neuron and pose it on new data vector:

$y_k := 1,\quad \underline{m}^T_k(t) := \underline{d}^T_k$

Actualize **j**-th row of intraconnection synaptic matrix **N:** Repeat **STEP 1.2.** with actual **t** parameter and setting **j = k** instead of **j = 1..m** at formulas

END;

$k = 1..m \mid y_k = 0$

2.3. Termination of iteration

IF $\sum_{j=1}^{m} y_j(t+1) \leq \lambda$ THEN GOTO STEP 3

ELSE **t:=t+1**, GOTO STEP 2.1

2.2. The F-Wing Fuzzy System

The basic concept of F-Wing is fairly similar to Kosko's FAM: create 'big hills' in the Cartesian product of the fuzzy system above cluster centroids discovered by unsupervised learning of a neural system. But we use different method achieving that goal, to avoid the difficulties detailed at critics of FAM. F-Wing creates the Cartesian product **C = { □(z),z | z∈T⊂R^n, □□z)∈[0,1] }** necessary for estimation putting down **□(z):T⊂R^n→[0,1]** fuzzy wing functions above the cluster centroids and web-edges of Straitjacket system:

- Support of a fuzzy wing function is a **B⊂T** hyperblock in the decision space called fuzzy wing hyperblock.
- Trace of the hyperblock is the Straitjacket-web edge between the **j**-th and **k**-th output neurons.
- Function value of the **jk**-th fuzzy wing above $\underline{\mathbf{m}}^T_j$ coordinate of **j**-th output neuron is always **1**. We call it 'from' neuron, because it acts as the centroid of **j**-th cluster.
- Function value of the **jk**-th fuzzy wing above $\underline{\mathbf{m}}^T_k$ coordinate of **k**-th output neuron is always **0**, and we call it 'toward' neuron because it acts as the final border of the **j**-th cluster in the given direction.
- The **jk**-th and **kj**-th fuzzy wings have the same hyperblock.

Horizontal axises are decision variables, vertical axis is membership value. Coordinates of 'from' output neuron $\underline{m}^T_j$ = (131,418) and 'toward' output neuron $\underline{m}^T_k$ = (259,450). The hyperblock of fuzzy wing is [131,259] × [418,450] (filled with gray). Output neurons are in opposite corners of the hyperblock. Its trace is an edge of the Straitjacket-web.

Fuzzy wing functions mean more difficult approach than fuzzy hyperpyramids which are usual most of the fuzzy systems and are assembled from partial fuzzy sets with a very simple operator. We rejected fuzzy hyperpyramids because of their inefficiency to model slim hypersurfaces transversal to coordinate axises

F-Wing creates a difficult hypersurface from fuzzy wings. Estimating output variable(s) from vector of input variables ($\underline{\mathbf{e}}$) means that we search the highest membership valued intersection of fuzzy hyperblocks and the hyperplane **E** created by $\underline{\mathbf{e}}$. We use simple sequential search to determinate the maximum instead of analytical optimization. Nevertheless, estimation is quiet a fast out of two reasons detailed at STEP 1 and STEP 2:

(All symbols defined at Straitjacket algorithm are valid except index **f,** numbers **a, b, g.**)

<u>Indexes:</u>

i = 1..s, 0 < s < n - index of the input variables

i = s+1..n - index of the output variables

<u>Inputs and parameters:</u>

Outputs of Straitjacket system:

$\underline{\mathbf{m}}^T_j(\mathbf{t})$ **j=1..m | y_j(t)=1** - cluster centroid coordinate vectors

$\underline{\mathbf{y}}(\mathbf{t})$- output neuron field membrane vector

0 < □□- degree of fuzziness of the system (near 0 - crisp, ∞ - fuzzy)

$\underline{\mathbf{e}} = (e_1,..e_s)$ - actual input vector of estimation

<u>Other symbols:</u>

$\underline{\mathbf{g}} = (g_{s+1},..g_n)$ - output vector needs to estimate

$\underline{\mathbf{c}}_{jk} = (c_{1jk},..c_{njk})$ - base point of **j,k**-th fuzzy wing

o_{jk} - number of partial intersections at **j,k**-th fuzzy hyperblock

$\underline{\mathbf{a}} \in R^s$, $\underline{\mathbf{b}} \in R^n$ -vectors

STEP 1 Determining indexes of partially intersected fuzzy wing hyperblocks

We take in consideration only that fuzzy wing hyperblocks which are at least partially intersected by hyperplane **E.** We measure degree of intersection at every fuzzy wings counting the variables where the intersection exists.

The **jk**-th fuzzy wing hyperblock is:

$$B_{jk} = \{\underline{b} \mid b_1 \in [m_{1j}, m_{1k}], .. \, b_n \in [m_{nj}, m_{nk}]\}$$

$$j = 1..\, m,\ k = 1..\, m,\ j \neq k,\ y_j(t)=1,\ y_k(t)=1$$

Input vector **e** generates a hyperplane in the space of input-output variables:

$$E = \{\underline{a} \mid a_i = e_i,\ i=1..s\}$$

Number of partial intersections at **j,k**-th fuzzy hyperblock

$$o_{jk} := \sum_{i=1}^{s} \left(1 \middle| e_i \in \left[m_{ij}, m_{ik}\right]\right)$$

$$j = 1..\, m,\ k = 1..\, m,\ j \neq k,\ y_j(t)=1,\ y_k(t)=1$$

Index of partially intersected hyperblocks by **E** are:

$$(j,k)^* = j,k \mid j = 1..\, m,\ k = 1..\, m,\ j \neq k,\ y_j(t)=1,\ y_k(t)=1,\ o_{jk} \geq 1$$

STEP 2 Determining base points of fuzzy wings

It is enough to compute the function value of **jk**-th fuzzy wing only in one base point It is the nearest point - measured by Euclidean distance - on hyperplane **E** to the trace of the **jk**-th hyperblock. Fuzzy wing function value is always maximal above the trace taking any possible intersection of the hyperblock parallel with coordinate axises.

$$c_{i(jk)^*} := \begin{cases} e_i & if \quad 1 \leq i \leq s \\ \dfrac{\sum_{i=1}^{s} e_i}{s} & if \quad s < i \leq n \end{cases}$$

$$\forall (jk)^*,\ i = s+1..n,\ i = 1..s \mid e_i \in [m_{ij}, m_{ik}]$$

STEP 3 Calculating membership function values of base points with the help of fuzzy wing function

$$\mu\left(\underline{c}_{(jk)^*}\right) := \frac{o_{(jk)^*}}{n} \times \left(\underset{i=1}{\overset{n}{MIN}}\left(h_{i(jk)^*}\right)\right)^{\chi} \times \left(\frac{\underset{i=1}{\overset{n}{MIN}}\left(h_{i(jk)^*}\right)}{\underset{i=1}{\overset{n}{MAX}}\left(h_{i(jk)^*}\right)}\right)^{1/\chi}$$

where: $\forall (jk)^*$

$o_{(jk)^*}/n$ - degree of partial intersection between **E** and the **jk**-th fuzzy hyperblock

□□□□□□- degree of fuzziness

$$h_{i(jk)^*} := \begin{cases} \left| \dfrac{c_{i(jk)^*} - m_{ik}}{m_{ij} - m_{ik}} \right| & if \quad m_{ij} \neq m_{ik} \\ 1 & if \quad m_{ij} = m_{ik} \end{cases}$$

$$\forall (jk)^*,\ i = s+1..n,\ i = 1..s \mid e_i \in [m_{ij}, m_{ik}]$$

STEP 4 Determining the output vector

Compatibility index of the output vector:

$$CIX\left(\underline{g}\right) := \mu\left(\underline{c}_{(jk)^{\max}}\right) = \underset{\forall (jk)^*}{MAX}\left(\mu\left(\underline{c}_{(jk)^*}\right)\right)$$

It is the maximum of the membership values of base points. That way, CIX measures degree of compatibility of the estimation result **g** to the best fitting cluster centroid $\mathbf{j^{max}}$. Crisp, estimated output vector:

$\mathbf{g_i := c_{i(jk)}^{max}}$ **i = s+1..n**

<u>Computational and memory requirement:</u>

Max CPU Time = T × □ × (□ - 1) × [s + 3n]

where:

T - time necessary for retrieve a numeric value

Memory Requirement = NUM × □□× (n + 1)

where:

NUM - memory space necessary to store a numeric value

F-Wing works faster and requires less memory space than FAM at higher number of decision variables. F-Wing examines always maximum □ **× (□ - 1)** fuzzy wings in their base point to complete one estimation, against FAM system, which treats around $\mathbf{5^{n-1}\times 2}$ fuzzy hyperpyramids, as we detailed at the critics of Kosko's system.

3. An Improved Particle Swarm Algorithm

Particle swarm optimization (PSO) was first introduced by Kennedy and Eberhart in 1995 [14]. The method was discovered through simulation of a simplified social model. Later on, it was developed as a general heuristic exploration technique, which performs effective exploration through memory and feedback. With the imitation of the behavior of bio-community, it enjoys a rapid calculation and a sound global exploration when applied in a large-scale optimization. Like evolutionary algorithms, PSO technique conducts search using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. During the calculation, the particle is affected by three factors when it is moving in space. One of the factors is the particle's current velocity $V(t)$. Another is the optimal point $pbest_i = (pbest_{i,1}, pbest_{i,2}, \cdots, pbest_{i,j})$ where the particle has reached before. The third factor is the optimal point $gbest = (gbest_1, gbest_2, \cdots, gbest_j)$ of the community or the sub-community. The particle's velocity is changed towards $pbest_i(t)$ and $gbest(t)$ in every iteration step. Meanwhile, V_i 、 $pbest_i(t)$ and $gbest(t)$ are assigned separately a weight at random. The velocity and position is updated according to the formula (2) and (3).

$$\begin{aligned} v_{i,j}(t) &= w \times v_{i,j}(t-1) \\ &+ c_1 \times r_1 \times (pbest_i(t-1) - x_{i,j}(t-1)) \\ &+ c_2 \times r_2 \times (gbest(t-1) - x_{i,j}(t-1)) \end{aligned}$$

$$x_{i,j}(t) = x_{i,j}(t-1) + v_{i,j}(t)$$

$$(i = 1,2,\cdots n \quad j = 1,2,\cdots m)$$

Where,

c_1, c_2 are the learning factors, generally, $c_1 = c_2 = 2$.

w is the weight scale operator.

r_1, r_2 are the randoms within the interval of [0,1].

t is the number of iteration.
n is the number of particles.
m is the number of dimensions.

Some scholars studied the nonlinear programming problem adopting the particle swarm optimization (PSO). Generally, they believe that parameter *w* is the key factor to affect the convergence of PSO [15]. In fact, the larger scale contributes to the searching for the global optimal solution in an expansive area, but its precision is not that sound because of the rough search. The smaller scale improves the precision of the optimal solution, but the algorithm may be trapped in the local optimization. Therefore, this paper provides self-adaptive weight scale, large enough to assist the algorithm to search for the optimal in a wide space at the very beginning of iteration. While the generations of evolution increase, the weight scale will be shortened by itself to increase the precision of the optimal solution. The formulation of the self-adaptive weight scale can be expressed as follow.

$$w(t) = w(0)\exp(-\rho \frac{t}{N_{\max}} + \eta)$$

Where,
t is the current number of evolution generations.

$N_{\max}$ is the total number of evolution generations.

ρ, η are control parameters.

The procedure of the self-adaptive PSO for combined forecasting model weight optimization can be described as follows.

Step1 Initialization: Set t=0. Let $X_i = \{\omega_i^j\}$ be a particle, generate randomly *n* particles $\{X_i(0), i = 1, \cdots n\}$ (set *n* to 20 in this paper). All particles are set between the lower and upper limits. Similarly, generate randomly initial velocities of all particles, $\{\vec{V}_i(0), i = 1, \cdots n\}$, where $\vec{V}_i(0) = \{\vec{v}_{i,1}(0), \cdots, \vec{v}_{i,m}(0)\}$. $\vec{v}_{i,k}(0)$ is generated by randomly selecting a value with uniform probability over the *k*th dimension $[-\vec{v}_k^{\max}, \vec{v}_k^{\max}]$.

Each particle in the initial population is evaluated using the equation (1).

For each particle, set $pbest(0) = X_i(0)$ and $J_i^* = J_i, i = 1, \cdots n$.

Let $J^{**} = \min\{J_1^*, \cdots J_n^*\}$. Set the particle associated with J^{**} as the global best, $gbest(0)$.

Step2 Velocity and Position updating: Let t=t+1. Using the global best and individual best of each particle, the *i*th particle velocity and position in the *j*th dimension is updated using the equation (5)-(7).

$$\begin{aligned} v_{i,j}(t) &= w(t-1) \times v_{i,j}(t-1) \\ &+ c_1 \times r_1 \times (pbest_i(t-1) - x_{i,j}(t-1)) \\ &+ c_2 \times r_2 \times (gbest(t-1) - x_{i,j}(t-1)) \end{aligned}$$

$$x_{i,j}(t) = x_{i,j}(t-1) + v_{i,j}(t)$$

Where:

$$w(t) = w(0)\exp(-\rho \frac{t}{N_{\max}} + \eta)$$

Step3 Individual and global best updating: Each particle is evaluated according to its updated position.

If $J_i < J_i^*, i = 1, \cdots, n$, then

$$pbest_i(t) = X_i(t)$$
$$J_j^* = J_j$$

Else go to *Step3*

Search for the minimum value $J_{\min}$ among J_j^*.

If $J_{\min} < J^{**}$ then

$$gbest(t) = X_{\min}(t)$$
$$J^{**} = J_{\min}$$

Else go to *Step3*.

Step4 Stopping criteria: If one of the stopping criteria is satisfied then stop. Else go to *Step2*

4. Numerical examples

The algorithm described above has been implemented in shanghai grid of East China area to forecast the 96 load data value of the day, 15.04.2003. Using the forecasting erros induced by the ARMA, RM, ANN to optimize the weight factors of the CM. Fig 2 is to show the forecasting error curve of the above four approaches. Tabl.1 gives the results under optimal weight factors based on the CPSO and New PSO approach.

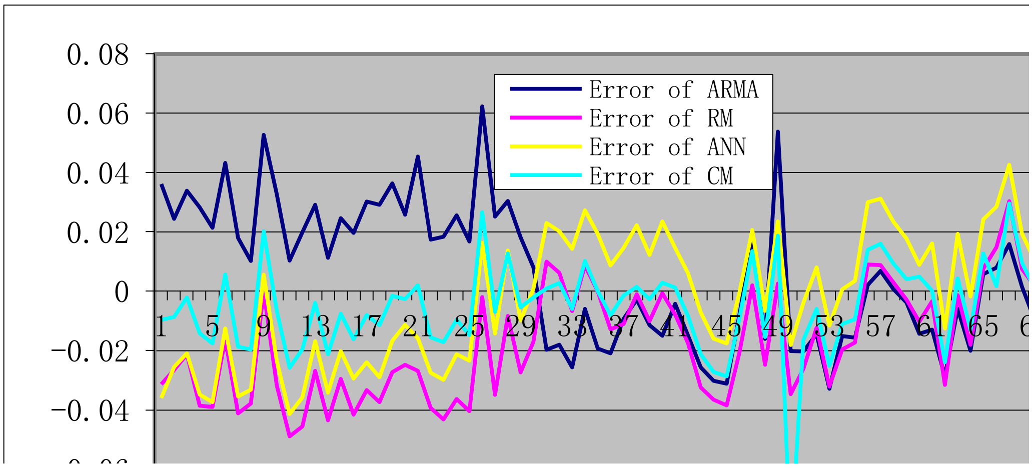

Fig 2. Error curves of four models

Table. 1. Forecasting results of various models

Methods	ARMA	RM	ANN	CM (CPSO)	Proposed
Mean error	0.020755	0.024065	0.02034	0.01567	0.01273

Maximal error	0.062328	0.052580	0.04987	0.04321	0.03872

Each algorithm is iterated 40 times in order to compare the CPSO with New PSO in terms of the convergence character and the computation speed. Table. 2 gives the average values for comparison showing that the New PSO is more efficient than CPSO.

Table 2. Performance of New PSO and CPSO

	Mean iterative	Mean time (s)
CPSO	>42	2.632
Proposed	<10	1.754

5. Conclusion

The Electric load series always presents complex phenomenon because of the influence of many complicated facts. The combined forecasting model is recognized as an appreciative method. The paper introduces an improved Particle swarm optimization (PSO) for electric load combination forecasting model weight optimization. The proposed approach based on the PSO is efficient in compute the weight factors of the CM and the introduction of the self-adaptive weight operator into the CPSO can largely improve the convergence speed of the PSO.

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