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Nonlinear Related Constraint Analysis of Hot Rolling Machine Running States

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Abstract: The parameters of rolling force , width and density control system should be set according to rolling technology, but in practice they tend to deviate from the set points because of various disturbance. The paper intends to make a full analysis of the rolling states by applying data fusion method and database of the distributed data acquisition system via rolling technology parameter interrelated constraint equations, and also renders an important reference to further optimize the rolling parameters.

Key words: rolling state; data fusion; interrelated constraint; neural network

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热轧机组运行状态非线性相关约束分析

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摘要: 热轧带钢生产线各机架轧制力、板宽、板厚控制系统,须根据轧制工艺计算设定参数.但在实际运行中,由于各种干扰因素的影响,往往偏离系统设定值,本文根据分布式数据采集系统的基本数据库,通过轧制工艺参数约束方程,运用数据融合方法,对实际轧机运行状态作出综合分析,为进一步优化轧机运行参数提供重要参考.

关键词: 轧机状态; 数据融合; 相关约束; 神经网络

1 Introduction

In general, a hot continuous rolling production line is about 1km long, and the running parameters of all the rolling machines on the rolling line should be computed and set according to rolling technology, which are correlated with a technology constraint. The paper intends to make a full nonlinear analysis by means of neural network information fusion by applying the real-time running state signals, which include rolling force , steel width, density, steel velocity etc, based on a distributed measurement system[1] for 1580 rolling production line, the given results renders an important reference to optimize the rolling parameters progressing.

2 Data fusion technology

Multi-sensor information fusion can extract more reliable and valid information than the single sensor by means of different types or located at different positions because different sensors have their own functions and the supported information is supplementary. At present, the multi-sensor information technique is widely applied in smart robot control, image processing and battlefield data analysis, etc. The current data fusion arithmetic can be classified into three types: probability model method, LSQ method and other advanced methods[2], etc. The probability model methods include robust statistic algorithm and recursive control algorithm, etc. LSQ methods contain Kalman filter, optimization theory and production rule, etc. The third applies fuzzy neural network or other intelligent processing algorithm, since its deductive process is close to thinking process, which presents a new approach for information fusion.

3 Rolling machine parameters and the interrelated constraint analysis of the running states

In the production process of strap steel, the measurement and control system for each rolling machine on the

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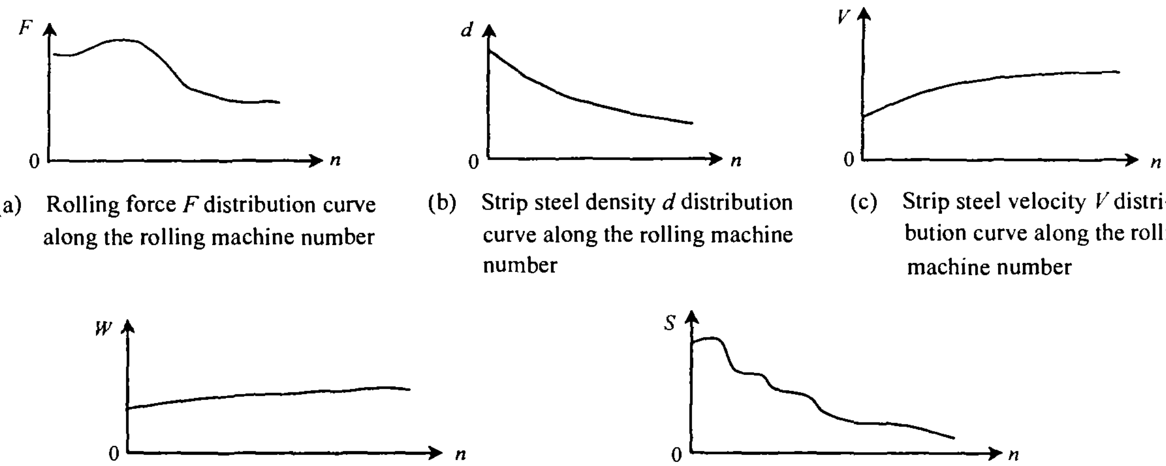
production line should be established according to rolling technique to ensure the product meets the planned specification. The main parameters for each rolling machine includes: rolling force, strap steel width and density, strap steel velocity, rollpass control, strain control, etc. The signals of the same rolling machine are mutually correlated and so are the corresponding signals of different rolling machines on the production line. The different specification of production has its own setting value. Take some strap steel specification as an example. We may draw out the corresponding signals distributed curve with rolling machine number as X coordinate and the distributed curve are shown in Fig. 1.



(a) Rolling force F distribution curve along the rolling machine number

(b) Strip steel density d distribution curve along the rolling machine number

(c) Strip steel velocity V distribution curve along the rolling machine number

(d) Strip steel width W distribution curve along the rolling machine number

(e) Rollpass distribution curve along the rolling machine number

Fig. 1 Distributed curves of rolling machine parameters

Obviously only if the signals fill in rolling technique constraint, the output production quality could be guarenteed. The main correlated relations are as follows:

1) Metal flux equivalence.

In order not to produce steel stack and steel drag in the continuous rolling production process, the strap steel velocity should conform to the principle of metal flux equivalence at the entry and output of each rolling machine on the continuous rolling production line.

That is:

$$W_{i-1}D_{i-1}V_{i-1} = W_iD_iV_i = W_{i+}D_{i+1}V_{i+1}, \quad (1)$$

$$w_id_iv_i = W_iD_iV_i. \quad (2)$$

W_i — entry strap steel width of number i rolling machine; D_i— entry strap steel density of number i rolling machine; V_i — entry strap steel velocity of number i rolling machine; w_i — output strap steel velocity of number i rolling machine; d_i — output strap steel density of number i rolling machine; v_i — output strap steel velocity of number i rolling machine; i — rolling machine number.

In the real rolling production process, the above relations can not be held entirely because of various disturbances, especially in the dynamic process. Consequently, the corresponding compensation methods should be adopted according to technical model.

2) Control constraint between rolling force F and rollpass location.

Rollpass location control constraint is as follows

$$d_i = S_i + F_i/M_i, \quad (3)$$

where F_i —the rolling force of number i rolling machine; S_i —rollpass of number i rolling machine; d_i — strap steel output density; M_i —the roll elastic coefficient.

Rolling force is associated with rollpass and the slab ingredient, for some specification of slab, the greater the rollpass, the greater the required rolling force, whose relation is shown in Fig. 2.

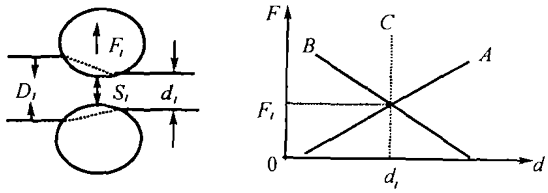


Fig. 2 Constrained relation curve between rolling force F_i and strip steel density d_i

Line A in Fig. 2 denotes constrained relation of formula (2), line B expresses the relation between the output density d and rolling force F when the strap entry density D hold invariable for some specification of steel slab, its cross-point represents the needed rolling force of the rolling machine.

3) Control constraint between the width and density of rolled steel.

The strap steel output density and width of each rolling machine are set and controlled by means of slab shape control model for the modern rolling production. The control model is very complicated and generally described with a multi-variable nonlinear equation set.

4) Compensation of lower shift change rate, velocity change and rolled steel end.

In the rolling process, the corresponding dynamic compensation are made to overcome the change of the dynamic parameters such as : when the rollpass has a change, the slab velocity compensation must be made; when the rolling machine speeds up or down, the rolling force should be regulated; while strap steel end departs from the rolling machine, the rolling force should be redeemed since the rolling force has changed to zero.

In summary, the rolling states on rolling production line are strong coupling nonlinear relation, which can be expressed with an integrated nonlinear function:

$$f(F,S,D,W,V,d,w,v) = 0, \qquad (4)$$

where F,S,D,W,V,d,w are vectored, for example: $F = (F_1, F_2, \cdots, F_n)^{\mathrm{T}}$ due to the effect of various disturbances, especially in the dynamic process, its actual state constrained equation can not be satisfied for formula (4) wholly, that is

$$f(F,S,D,W,V,d,w,v) \neq 0,$$

where f is a complicated multi-variable nonlinear equation, which is highly inconvenient to solve directly; in order to simplify the above equation , the paper adopts decomposition with rolling machine number, namely, for every rolling machine, a nonlinear state constrained equation is set up respectively.

$$f_k(F_k, S_k, D_k, W_k, V_k, d_k, w_k, v_k) = 0. \qquad (5)$$

According to the realtime measurement data, we compute the deviation of the correlated equation and draw out its distributed graph, on the basis , we may study its dynamic distribution law and the parameters change tendency of a rolling machine with time.

In order to evaluate the whole rolling state, we make the following definition:

$$\| f' \| = \sqrt{\sum_{k=1}^{n} \| f_k \|^2} \ (k = 1 \sim n), \qquad (6)$$

where n means the sum of rolling machines on the production line, f_k denotes the relative deviation from normal state constraint of number k rolling machine, $\| f' \|$ expresses the mean square error of all rolling machines relative deviation from normal running state for whole rolling line, which represents the deviation dgree of whole rolling line running state from normal state, therefor, it is reasonnable that $\| f' \|$ is adopted as the metric space standard of rolling line running state deviation from standard state value.

4 Rolling machine states analysis with data fusion based on neural network

4.1 Data fusion model based on neural network

It can be known from the analysis of Section 3 that the running state constraint equation is a classic nonlinear strong coupling relation. The paper applies three layer of feedback neural network shown in Fig. 3 to make data fusion for each rolling machine, on the basis, set up running state constraint model, then, to work out synthetic analysis.

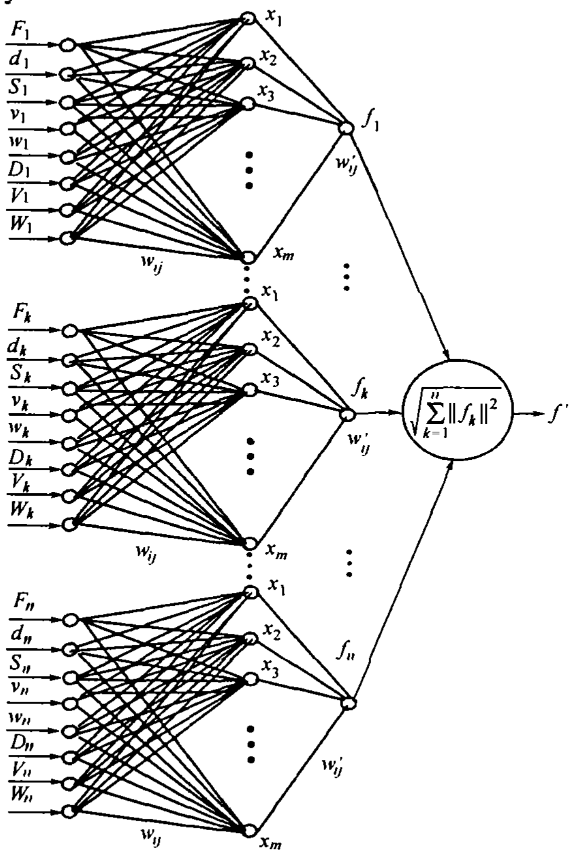


Fig. 3 Neural network data fusion model of rolling states

1) Training sample.

We select 200 sets of measurement data as training sample, and set $f_k = 0.01$ ($k = 1, 2, \cdots$), compute the neural network parameters for each rolling machine and the correspond theoretical set data is used as checking sample.

2) Make offline computation to determinate w'_{ij}, w_{ij} and b_j with application of BP algorithm.

3) S type of concealing node function is adopted

$$g(x) = \frac{1}{1 + e^{-x}}. \tag{7}$$

Select error $E = 0.4 \times 10^{-2}$. By means of off-line simulation we obtain a result: when the mean node $m = 6$, the required computation quantity is the smallest. Thus, the mean node m is selected as 6.

As an example, we select the data of the fifth set of rolling machine to compute neural network parameters, the last results are shown as Table 1 and Table 2.

Table 1 w_{ij} training results

	i				
	1	2	3	4	5
1	0.23	0.27	0.22	0.36	0.42
2	0.31	0.25	0.24	0.29	0.38
3	0.19	0.16	0.28	0.24	0.33
4	0.17	0.13	0.16	0.18	0.32
5	0.05	0.09	0.14	0.17	0.32
6	0.08	0.07	0.09	0.11	0.23

Table 2 w'_{ij} and B_i training results

w'_{11}	0.51	B_1	0.64
w'_{21}	0.53	B_2	0.32
w'_{31}	0.65	B_3	0.81
w'_{41}	0.24	B_4	0.72
w'_{51}	0.86	B_5	0.63
w'_{61}	0.11	B_6	0.54

4.2 The running state analysis of rolling machine

The fundamental running data of rolling machine is obtained from an on-line distributed measurement system[2], when the neural network model is plugged in the application software as a function block, we can carry out the on-line analysis of the running state. Fig. 4 displays the analyzing result graph of running state at a given time which is computed with the former neural network data fusion model, where: $\| f' \| = 0.298$, $f_7 = 0.25$ denotes that the relative deviation value from the normal running state is 0.298 for whole running line and 0.25 for seventh rolling machine. It can be seen that the running state deviation of the seventh machine is the greatest, and real system recorder shows that the seventh rolling machine happens to be faulty, which is consistant with the analyzing result.

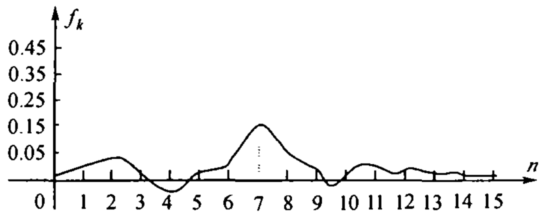


Fig. 4 Difference distribution of rolling machine running states

5 Conclution

The paper makes use of real-time running state data to make a real-time analysis of running state by means of neural network data fusion technique, work out a metric standard of deviation from normal running states; its analysis results have a high pretty reference value to enhancing production efficiency and optimize the whole device operation. It is studying how to determine the optimizing parameters of next rolling procedure according to $\| f' \|$ and the distributed state of f_k.

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