The Application of Dynamic Model Based on Neural Network & Knowledge Base for LD Converter

(Revised Version)

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Abstract: Current LD dynamic algebraic model used by Baosteel Corp. shows a variety of disadvantages. A new dynamic model based on neural network and knowledge base is therefore designed. Excellent simulation result and satisfatory online testing report are obtained by the new model. Besides, a skillful numeric method is used to solve the inverse problem of neural network

Keyword: LD Converter, Dynamic Model, Neural Network, Knowledge Base

Introduction:

In the past years, tremendous effort has been devoted by steel companies to improving the productivity in every key links of steel production, such as BOF (Blowing of Furnace), secondary metallurgy and continuous casting. Take BOF for an example, technicians depend heavily on a sublance device, which measures carbon content and temperature 2 to 3 minutes before the end of blowing, to properly control BOF process. Many dynamic models are based on sublance information to predict the necessary oxygen and coolants shortly before the end of blowing. The current model developed in this paper is a dynamic model based on neural network and knowledge base (NNKB). NNKB is mainly applied in LD converters and the corresponding online test in BaoSteel Corp.

Since1985, BaoSteel has been using a dynamic model imported from Japan, which uses an exponential function for decarburization and a linear equation for bath temperature prediction. One of the features of this model is that it can self-adjust its parameters as long as heat data in different periods are sequentially related. However, a statistical analysis shows that the sequential correlation is not significant in the practice of BaoSteel. As a result, the self-adaptive parameters generated by the model sometimes aren’t convergent so that the engineers have to reset all the parameters according to their own judgement. This creates a lot of uncertainty of production as engineer’s estimation could be biased and leads to very low endpoint-hit ratio. Thus BaoSteel was in an urgent demand of a new model. Furthermore， a new environmental friendly process LT was introduced into two BOFs of BaoSteel. These BOFs are required to use up to 5 different coolants at the late period of blowing. However the Japanese model can only calculate one coolant. Thus a new dynamic model is expected to take this new situation into consideration.

We first gathered over 12000 heat data from online database and tried to improve the Japanese model. Table 1 lists four optimizing methods for that model. However, both hit ratio and R square do not meet the requirement.

Table 1: Optimized Algebraic Model for Carbon Content and Temperature

Optimized Structure and Method	Optimized Results	
	Simulation Hit Ratio	R Square
Separate Grade with Imported Models	C 70%	0.1
	T 60%	0.18
Imported Temperature Model with Quadratic Item	T 63%	0.15
Imported Models with Clustered Data	C 72%	0.2
	T 62%	0.16
Imported Temperature Model with Clustered Data and Quadratic Item	T 65%	0.22

Note: The definition of R Square: $R^2 = 1 - \frac{\sum(y - \hat{y})^2}{\sum(y - \bar{y})^2}$ *Higher R Square generally indicates higher accuracy of the model.*

Then we began to consider general neural network (NN) technology that is believed to be able to theoretically approximate any non-linear system. However, the NN simulation result is not satisfactory due to data noise. We need a technology to screen out noise and get better data. As a solution to this problem, we combine neural network with knowledge base. The new model achieves great success. Please refer to table 2 to view details. Figure 3 and Figure 5 show the corresponding simulation curve.

Table 2: Dynamic Models Combining Neural Network and Knowledge Base

Model	Carbon Content	Temperature
Input Variables	WST , TC1, TVO,C1	WST, T1, VO, FluxT,
Size of Total Samples	866	1560
R Square	0.6210	0.7909
Hit Ratio for T±10°C and C±0.01%	98%	96%
Size of Prediction Set	173	312
R Square	0.6000	0.8149

Hit Ratio for T+10°C and C+0.01%	97%	94.6%

Notation:

WST: weight of molten steel and scrap
VO: volume of blowing oxygen
T1: sublance temperature in blowing
C1: sublance carbon content in blowing
FluxT: temperature decrease coolants cause
TVO: blowing oxygen plus oxygen flux contains
TC1: C1 plus carbon ore contains

Combining Neural Network with Knowledge Base

It is clear that an accurate model builds upon good data. Good data means that data distribute normally and comply with manufacturing practice. As shown in table 3, the models that are built on raw data do not perform well: Both hit ratio and R Square are low. One reason is data noisiness. A lot of studies confirm that the online data deviate from real situation. In some cases, records are self-conflicting. Thus we were forced to find good representing data from all raw data if a high-accurate model is expected.

Table 3: NN models for temperature and carbon content using raw data

Model	Temperature	Carbon Content
Input Variables	WST, T1 , TVO, FluxT,	WST , TC1, TVO
Size of total samples	3130	1290
R Square	0.328	0.1959
Hit ratio for T+10°C and C+0.01%	70%	79.50%
Size of prediction set	626	258
R Square	0.3205	0.215
Hit ratio for T+10°C and C+0.01%	67.70%	78.30%

With the help of experienced furnace technicians and metallurgical engineers, a knowledge base is constructed. Currently, the knowledge base functions well in the following four aspects.

1. Determine Ranges of All Factors

Any information should be standardized as a decimal fraction between 0 and 1 in the model of neural network. Thus it is necessary to determine ranges of all factors in the stages of designing and application. Through querying from the knowledge base, ranges of all factors are obtained as table 4 shows. In the designing period, data are strictly kept within the ranges table 4 describes.

Table 4: maximum and minimum values of input variables

Factors	WST (100kg)	T1 (^oC)	C1 (0.001%)	VO (Nm^3)	Te (^oC)	Ce (0.001%)
Min Value	2500	1560	100	400	1650	30
Max Value	3500	1650	300	2500	1700	80

Notation:
Te: the end bath temperature
Ce: the end carbon content

2. Determine Model’s Input Variables

As we know, steel-making is a complicated nonlinear process. On the one hand, if too many factors are considered at the same time, it could be difficult to design a feasible model. On the other hand, the model couldn’t reflect the nature of steel-making if certain important factors are overlooked. Here are two examples showing how knowledge base helps determine model’s input variables.

C1 does not show up in algebraic model which determines endpoint temperature. However, knowledge base shows that the incremental temperature upon unit blowing oxygen varies with the current carbon content. Usually, incremental temperature upon same blowing oxygen is negative related to C1. Therefore, it is reasonable to choose C1 as input in the temperature model.

The carbon ore content is missed out in the algebraic model. In fact, 1000 kg ore will bring in additional 0.01% of carbon content while the initial carbon content ranges from 0.1 % to 0.3%. Therefore, it is necessary to take the carbon ore content into consideration when we designed the model of carbon content.

3. Adjust Technical Parameters

Technical parameters, including volume of oxygen brought into the converter and temperature drop of liquid at the time when a certain flux is added, are described by the metallurgic engineer and operator. This idea is very useful to simplify the online numeric algorithm.

4. Eliminate Abnormal Data

Knowledge base contains many rules describing the relationship between input and output. For instance, 100 Nm^3 oxygen will make liquid steel increase 4~6 ^oC. This kind of rule is very helpful to eliminate some abnormal data.

Design Neural Network Architecture

The general principle diagram of NN model is shown in figure 1.a. The neural network parameters are adjusted to minimize the square sum of prediction errors of temperature and those of carbon content.

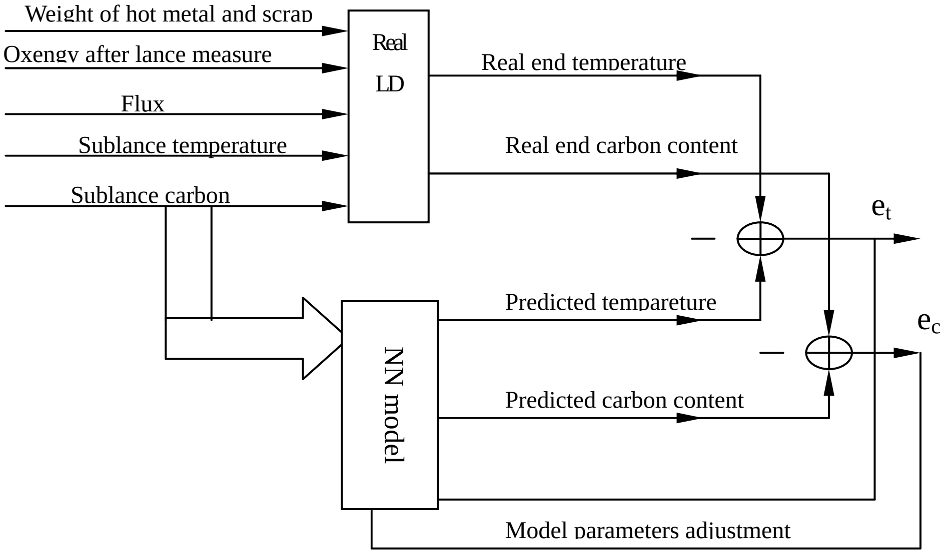

Figure 1.a general neural network modeling principle

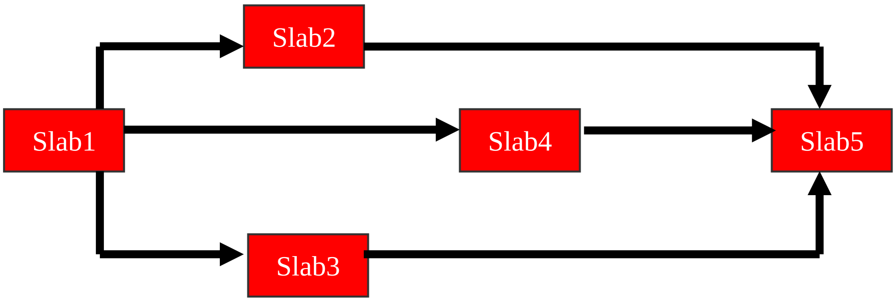

Figure 1.b Neural Network Architecture

BP network shown in figure 1.b is chosen to design dynamic control model for LD converter. Slab2, Slab3 and Slab4 are hidden slabs. The number of neurons and activate function of each slab are listed in table 5. As to input variables, please refer to table 2. The output variables of temperature model and carbon content model are ending temperature and ending carbon content respectively. The maximum value and the minimum value of each factor are listed in table 4. All pre-processed data is divided into three subsets for training, testing and predicting in the ratio of 3:1:1. Anyway, according to our experience, it is also difficult to improve accuracy of the NN model by changing NN structure and number of neurons and hidden slabs for the dynamic modeling.

Table 5: neurons number and activate function of each slab

Slab	Slab1	Slab2	Slab3	Slab4	Slab5
Activate function	Linear	Gaussian	Tanh	Gaussian comp	Logistic
Neuron number(temperature)	5	11	11	11	1
Neuron number(carbon)	3	11	11	11	1

Simulation Results for NN and NNKB

The simulation results for ending temperature based on NN and NNKB are shown in Figure 2 and Figure 3 respectively. Those of carbon content are shown on Figure 4 and Figure 5 respectively. The black points in the figures denote real data and the others denote predicted data. It is obvious that the results from NNKB model are much better than that from NN model.

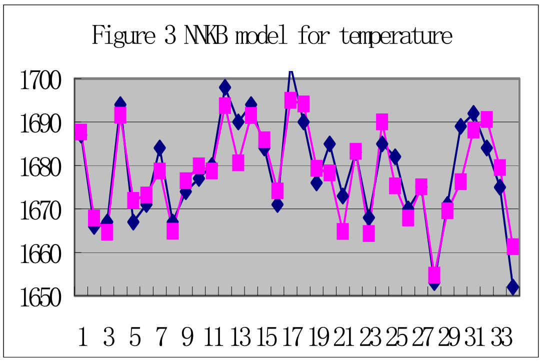
Figure 3 NNKB model for temperature

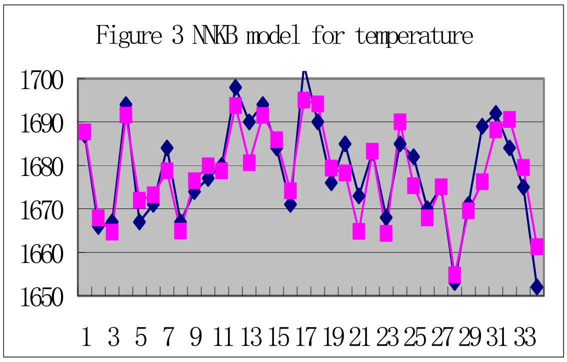
Figure 3 NNKB model for temperature

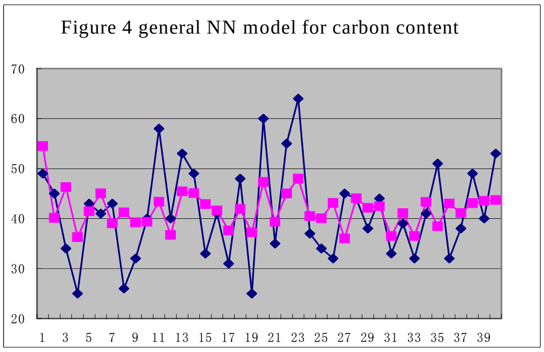
Figure 4 general NN model for carbon content

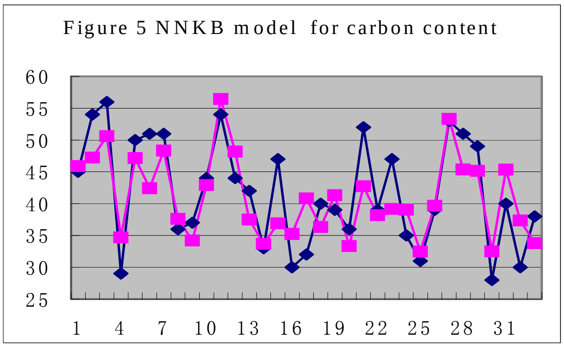
Figure 5 NNKB model for carbon content

Online Application of Neural Network Model

1. Solution to Inverse Problem

So far, we have got temperature model and carbon content model. If the values of input variables are known, we are able to estimate endpoint temperature and endpoint carbon content. But the issue of online application is just in the opposite way. The aimed bath temperature and carbon content are known while volume of blowing oxygen and flux are to be estimated.

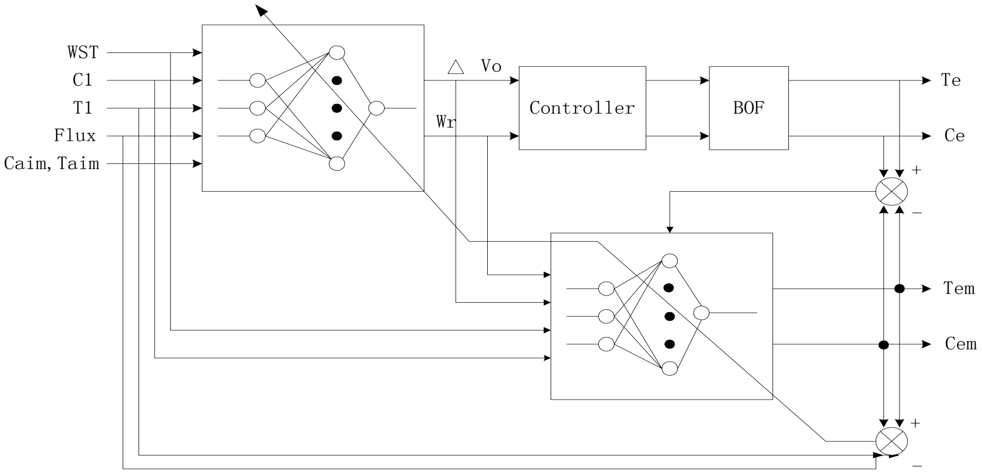

Figure 6

Usually a control engineer chooses a controller to implement NN model as shown in Figure 6. However, it runs at great risk at different levels. Firstly, the model connecting two neural network models seems too sophisticated. Secondly, it is not sure whether the model is stable and convergent. Lastly, it is very possible that there doesn’t exist solution to the model in some circumstances. However, if the controller structure shown in Figure 6 is abandoned, we will face the inverse problem of NN that has theoretically no good solution. Fortunately, the decarbonization process and temperature up process can be considered as monotone. Thus a numeric method is used to deal with the NN inverse problem.

The principle diagram of online NNKB model in process computer is shown in figure 7.

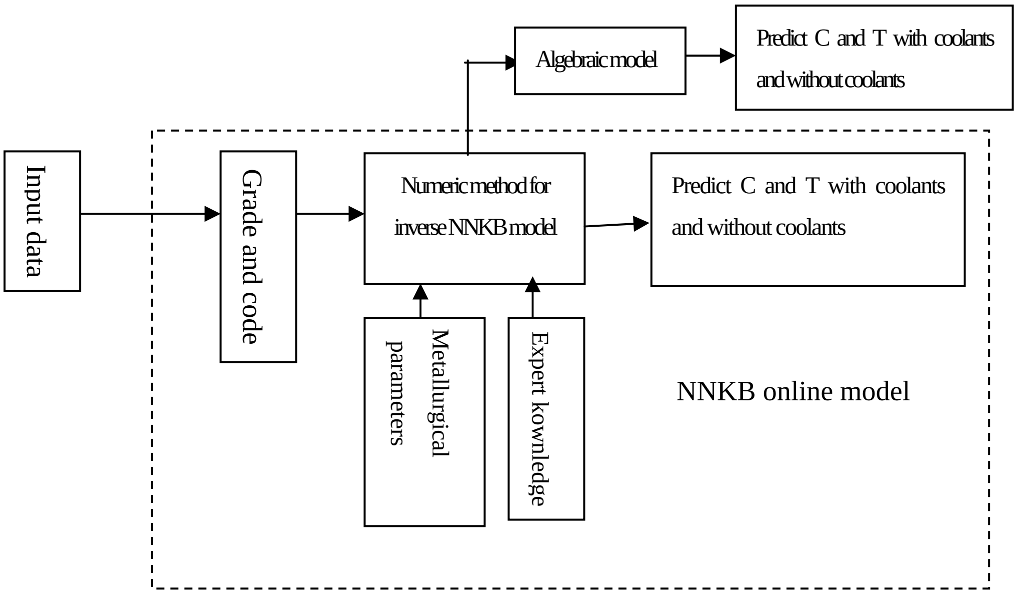

Figure 7 NNKB online model

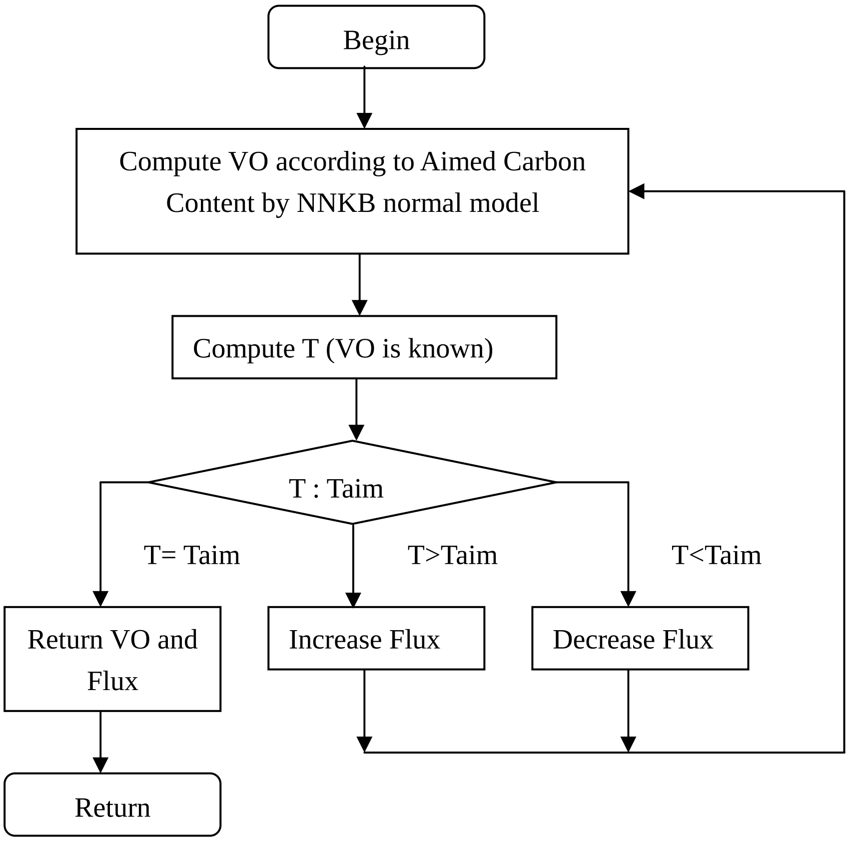

Figure 8 algorithmic to compute oxygen and flux

We also use the numeric method to compute volume of blowing oxygen and amount of flux. The flow chat (figure 8) roughly describes the algorithm.

2. Industrial Test and Online Development

Before online application on Open VMS with DEC FORTRAN, we firstly developed a NNKB model based on PC with Visual Basic for offline test. The industrial test was done in the late April 2000. Test results are shown in Figure 9 and 10 for temperature and carbon content. As we can see, estimations of NNKB model remarkably match real data. The real carbon content and temperature curve shown in the figures is very close to the simulation one. Currently operators begin to use the new dynamic model for reference. Now online NNKB model is under development, which will replace the algebraic model in July for No. 2 steel plant in BaoSteel.

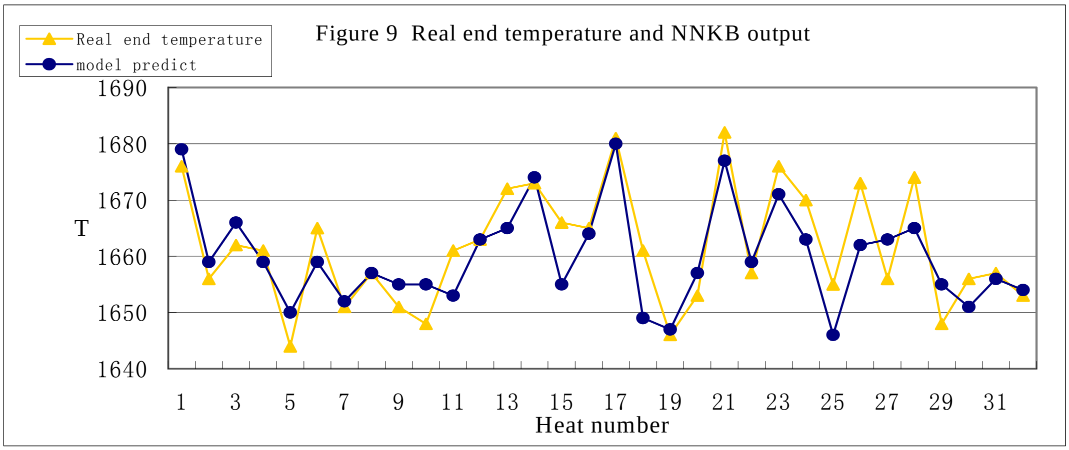

Figure 9 Real end temperature and NNKB output

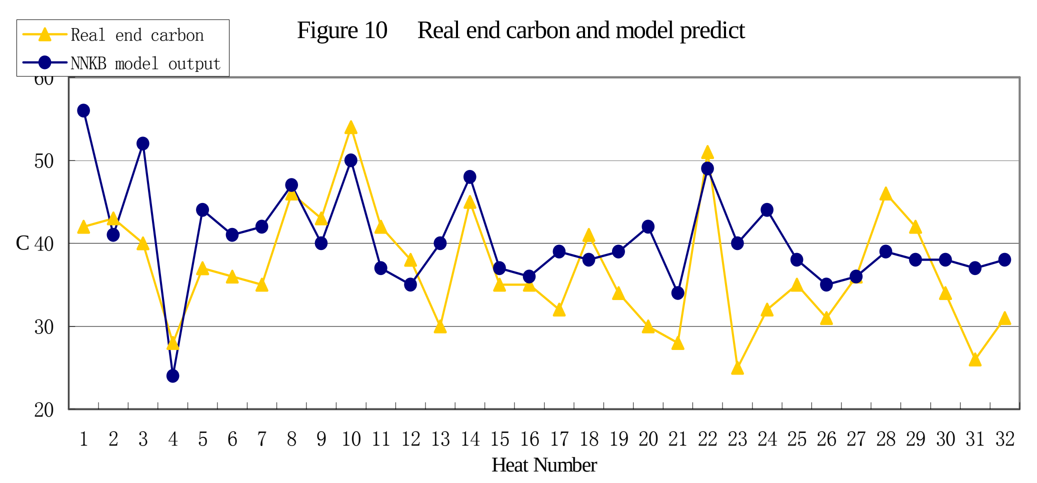

Figure 10 Real end carbon and model predict

Conclusion

Theoretically the neural network model can approximate any nonlinear system. However this method cannot work well with online LD dynamic model without extra methods because raw data from online database are often full of noise. Furthermore, according to our experience, it is difficult to improve accuracy of the NN model by simply changing NN structure and number of neurons and hidden slabs for the dynamic modeling. Fortunately, a combination of neural network with knowledge base modeling method shows very satisfactory results which are much better than the algebraic model both in the terms of simulation and real production test.