New Results in Control of Steady-State Large-Scale Systems

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Abstract: This paper reviews what the first Author and his Group have been investigating for the past fifteen years in the on-line steady-state hierarchical intelligent control and optimization of large-scale industrial processes (LSIP), or large-scale systems (LSS), viz., the use of neural networks for identification and optimization, the use of expert system to solve some kind of hierarchical multi-objective optimization problems, the use of the fuzzy logic control, and the use of the iterative learning control. Several implementation examples and the product quality control for LSS are introduced too. Finally the paper suggests the new stage of development.

Keywords: Large-scale systems, industrial control, intelligent control, optimization, quality control

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1. Introduction

In the 7-th IFAC/IFORS/IMACS Symposium on Large Scale Systems Theory and Application, Beijing, China, Roberts, the first Author of this paper and Lin (1992) gave a plenary report entitled "Steady-state Hierarchical Control of Large-scale Industrial Processes: A Survey". It considered the development of hierarchical control of LSIP in three stages: static multilevel optimization stage, steady-state hierarchical optimization stage and integrated system optimization and parameter estimation (ISOPE) stage . Fifteen years and more have passed by since then. What has been emerging in this field? And what is the fourth stage if existed?

For the past decade, the intelligent control has been a very important research direction and pushing the control science and technology forward. So do the large-scale systems theory and applications. The steady-state intelligent control of industrial processes means the application of ideas and methodologies of artificial intelligence to steady-state hierarchical control of LSIP and LSS based on human experience and knowledge in control and decision. In other words the neural networks, the expert systems (the intelligent decision unit), the fuzzy logic control, the iterative learning control, the genetic algorithms etc. and their combinations are integrated with traditional analytical approach for solving the identification, control, optimization, coordination and fault diagnosis of LSIP and LSS (Wan, 1994). Since the beginning of 1990's the first Author and his Large-scale Systems Research Group have devoted themselves to the study of steady-state hierarchical intelligent optimizing control of LSIP and LSS for fifteen years. A brief summary of the main research results including the implementation examples in process industry and the conclusions is as follows.

2. Use of Neural Networks

2.1 Neural network modelling

The first Author's Group has successfully applied a multi-layer BP neural network for identifying a steady-state model of a hot-cold water mixer pilot plant that includes two subprocesses, heating and levelling, and conducted hierarchical optimizing control based on the neural network steady-state model by three microcomputers in hierarchy, and hierarchical steady-state stochastic optimizing control with variance analysis even if the data are corrupted by noise (Wang, Wan and Song, 1994).

For steady-state modelling of process possessing stochastic or chaotic steady-state behaviours, Luo, Liu and Wan (1998) have proposed an adaptive fuzzy neural inferring network (AFNI network) based on Takagi-Sugeno fuzzy model. And the Group have used the neural networks for product quality model and yield model for control of LSS.

2.2 Neural network optimization

Leung, Li and Wan (1993) have used the Hopfield neural network to fit the static optimization with the interaction prediction and the interaction balance coordination methods. The Lagrange multiplier, Kuhn-Tucker multiplier and relax variable are applied to treat constraints, and an energy function E is defined. Then by differentiating E with respect to output y, set-points c and the Lagrange multiplier, Kuhn-tucker multiplier and the relax variable, a set of differential equations are obtained. This set of differential equations is solved by Runge-Kutta method without iteration. It is because the differential equation represented by upper coordinative network and those represented by lower decision networks are solved step by step and simultaneously, and they interchange the integration information step by step within integration.

The first Author's Group have proved the stability and optimality of Hopfield network (Leung, Li and Wan, 1993; Li, Wan and Leung 1994; 1995; Wan and Huang, 1998). In addition, the Hopfield network has been extended to solve the steady-state optimizing control of LSIP with global feedback or local feedback. It requires 6 on-line iterations to obtain an improved suboptimal solution or 9 on-line iterations to obtain an optimal solution for a LSIP with three subprocesses, respectively. The former result is obtained by using the output shift method, while the latter by output shift and its partial derivative compensation.

3. Use of Expert System

Based on the expert system (rule-based system) an intelligent decision (ID) unit has been suggested to solve some kinds of optimization problems of LSIP and LSS. The ID unit is composed of a knowledge base, a database, an inference engine and a learning machine (Fig.1).

By means of the ID unit an intelligent interaction prediction method has been used to flexibly choose global coordinative variables for solving the hierarchical multi-objective optimization problem (Li, Qin and Wan, 1991). In the lower level the precise traditional optimization method is used for making a decision. The ID unit ensures the convergence of the algorithm and finds a satisfactory solution for the problem

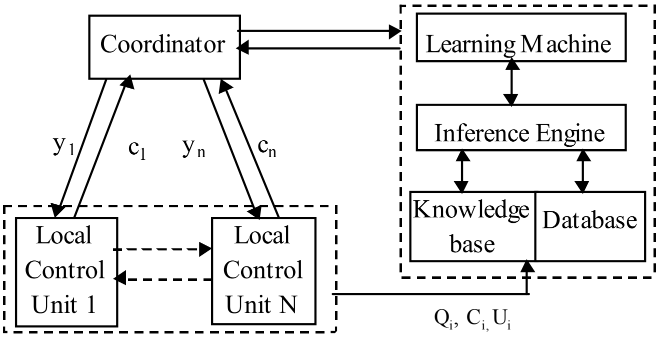

Figure 1. Large-scale system using ID unit

By the ID unit an intelligent coordination method with objective-modified has been used to steady-state optimizing control of LSIP and LSS. The idea is to use the objective or job of subprocesses or subsystem as the coordinative variable, then to combine it with traditional large-scale system theory in order to better adapt the change of the environment or the job (Li, Qin and Wan, 1992).

By means of the ID unit a hierarchical intelligent optimizing control method for steady-state multi-objective LSIP with fuzzy parameters has been suggested (Li, Qin and Wan, 1992). Generally there are several fuzzy parameters in the upper level, such as the cost parameter and the parameters in the upper global constraints, etc. A confidence level α is selected by which the problem is transformed into a crisp multi-objective optimization problem depending on α.

4. Use of Fuzzy Logic Control

The use of the fuzzy logic control benefits much by treating the model as that with fuzzy parameters characterized by triangle membership functions when the model-reality difference exists. Meanwhile the controller set-point *c*, the interaction output *y* and interaction input *u* are treated as the crisp variables. Then the programming problem formed by the steady-state optimization becomes one with fuzzy parameters. The problem is transformed into a solvable crisp programming problem after some fuzzy addition and multiplication operations. This approach requires less number of iterations and provides a better objective function to compare with those of the normal approach either in the open-loop hierarchical control case or in the closed-loop case using global feedback, and either by the interaction balance coordination, the interaction prediction coordination methods or by the mixed coordination method (Gu and Wan, 2000; 2001a; 2001b). It is necessary to point out that the double iterative algorithm for fuzzy models based on interaction balance method with global feedback requires the fewest number, about four, of on-line iteration so far.

5. Use of Iterative Learning Control

In hierarchical steady-state optimization closed-loop control or global feedback utilizes the real steady state output information to modify the model-based optimum. Thus the methodology needs usually several iterations to capture the applicable optimum. This means, for each iteration, every real subsystem must be stimulated simultaneously by the step-type set-point changes computed from the optimization layer without severe disturbance to LSIP. In order to improve the transient performance for the optimization programming to be applicable, an iterative learning control (ILC) strategy for LSIP in a decentralized mode has been proposed in article (Wan and Huang, 1998; Ruan, Li and Wan, 2003), i.e., there is an individual ILC unit and control action in each subsystem and further investigations have been addressed in literatures (Ruan, Wan and Gao, 2000; Ruan et al., 2005). The control structure is shown as in Figure 2 where SSI denotes the steady state information of the large-scale system. Optimization layer contains the coordinator and the local decision units .Subsystem denotes subprocess including its controller. D denotes the interaction between subprocesses. c denotes the set-point change. y_d denotes the desired trajectory. r_k denotes the control output of the ILC unit. y_k is the subsystem output.

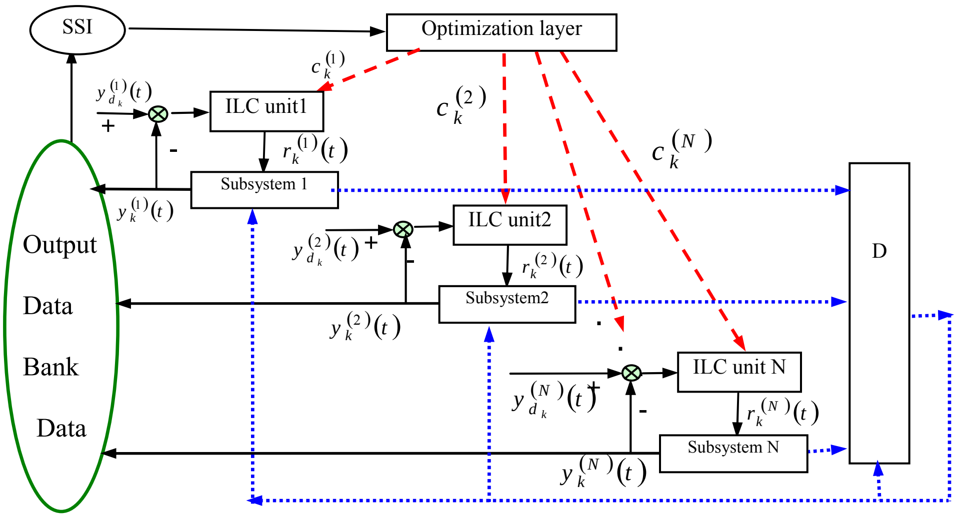

Figure 2. Iterative learning control structure for a large-scale system

In the studied iterative learning control strategies, the distinct magnitudes of the step-type set-point change sequence have been introduced to the proposed conventional PD-type open-loop ILC algorithm, higher-order ILC law as well as an optimal ILC rule. Instead of in the sense of λ norm the convergence analysis in the sense of Lebesgue-p norm is derived which evaluates the output error in the Lebesgue integral over the whole operation time interval and some remarks are discussed (Ruan et al., 2005, 2008a, 2008b). The studies have concluded that the proposed ILC may efficiently improve the transient performance, such as speeding up the transient rising, decreasing the overshooting and shortening the settling time, etc, while the step-type set-point change sequence drives the system consecutively for reaching the steady-state output without any steady-state error. The studies have also discussed the influence of the inherent characteristics of the system such as the interaction, multi-dimensionality as well as the distinct magnitudes of the set-point change sequence on the convergence despite that the studies may cover the existing result for robot to track a unique desired trajectory. For one of subsystems of a linear time-invariant large-scale system, the tracking behavior is shown in Fig. 3.

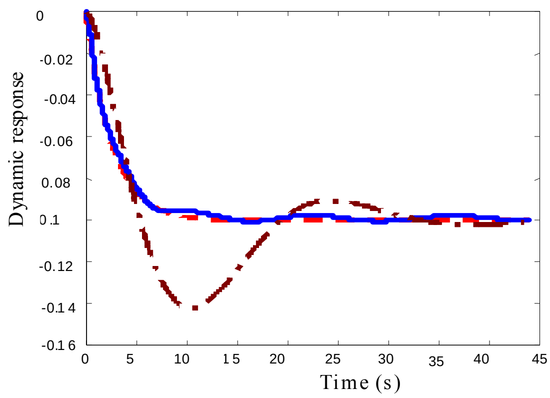

Figure 3. Output information at 8-th implementation

In Fig. 3, the dashed curve denotes the predetermined desired trajectory, the dashed-dotted curve represents the output driven by the step-type decision and the solid one is that of stimulated by the ILC generated signal, respectively.

Ruan et al. (2003) suggested a local-symmetrical-double-integral type iterative learning control for dynamics of industrial processes with time delay in the course of steady-state optimization when measurement noise is present.

This approach is a combination of study on the steady-state hierarchical optimization with that on the transient. It is evident that after seven ILC iterations the dynamic characteristics are greatly improved with two periods of set-points being provided by the coordinator in the Optimization layer of Fig.2. Furthermore, the first ILC iteration in the second optimization period is equivalent to the k+1-th iteration in the first optimization period if its number of iterations is k. Therefore the dynamic characteristics are further improved in the second period. Thus the whole set-point changes can once be fully imposed on the LSIP or LSS with little disturbance.

6. Applications in Industry

The first example is the steady-state optimizing control of a nickel flash furnace based on neural network models in a smelting plant (Wan, Wan and Yuan, 1999) which is located in Jinchang City, Gansu Province, China (Fig. 4). The quality model of the matte is based on three 5×5×1 BP neural networks.

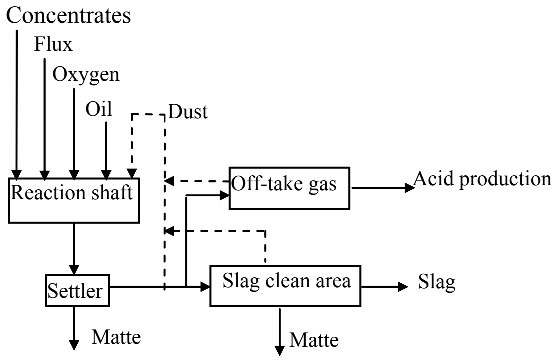

Figure 4. Nickel flash furnace system

The inputs of the quality model are the 4 manipulating variables and 1 disturbing variable, while 3-quality indexes (properties of matte) are the outputs. The matte yield model is based on a 5×5×1 BP neural network with yield as the output. Then the objective function is minimization of the total energy consumption of the furnace subject to the inequality constraints formed by quality submodels and quality index tolerances, and product yield model with yield not less than normal. The study and the industrial site experiment for the optimization of the furnace have obtained a satisfactory result.

Liu and the first Author (Liu and Wan, 1999) have given the second example in which a multi-layer BP neural network is used to identify the steady-state model of air preheater of a big power-station boiler under different load condition (Fig. 5).

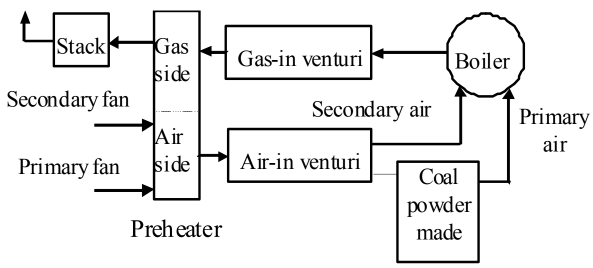

Figure 5. Boiler preheater system

The primary wind pressure and temperature, and the secondary wind pressure and temperature of the preheater are used as four inputs and the boiler-load is used as output of neural network. Both data can be measured for training neural network.

The sum of primary wind pressure and secondary wind pressure approximately represents the sum of the two wind motor currents is selected to be the objective function. The optimization is to minimize the sum of currents under a definite load condition and is carried out by an enumerative method within feasible region latticed by small intervals. Based on this model an on-line steady-state optimizing control is successfully applied. The intelligent optimization gives considerable profit by saving electricity, is really implemented in big power-station boilers in China as well as those exported to abroad.

7. Steady-State Identification

Chen and Wan (1995; 1999) have suggested an approach to identifying a steady-state model by the dynamic data acquired from the normal set-point changes during tuning or optimization. The input is of the step-function form. They have proved, however, that under mild conditions the steady-state model obtained from the approximate dynamic model is with the strongly consistent estimates.

To a class of nonlinear slow time-varying large-scale processes, which have many subprocesses interconnected with one another, a parallel two-stage identification algorithm has been studied. The consistency of the estimates and convergence of the parallel iteration are also proved.

In addition, the Research Group has given a new steady-state identification method that provides a steady-state model of a nonlinear process only using steady-state data from several set-point changes and the estimates are strongly consistent (Huang and Wan, 1997; see Chapter 2, Wan and Huang, 1998). Besides, Huang, Wan and Han (1994) have given a method different from the above by Chen and Wan to calculate the process derivative with respect to set-point only using steady-state data acquired from several times set-point changes and its strong consistency has also been proved.

8. Robustness of Optimization Algorithm

It needs to study robustness of an optimization algorithm with respect to model parameter and noise to avoid divergence. Xu and Wan (1994) have investigated the robust stability of the algorithms for steady-state optimizing control of industrial processes, discussed the dependence of the optimal solution obtained from the algorithms on the parameters λ that represent the characteristic numbers of noises or process structure parameters. The Pompeiu-Hausdorff hemidistance H of two optimal solution sets is used as a measure for the robustness of the algorithm with respect to λ. One is the optimal solution set, while the another is the optimal solution set perturbed by the parameter λ. Actually to calculate the hemidistance is rather difficult, if not impossible. Hence $\partial H/ \partial\lambda$ is used as a sensitivity index to compare different optimization algorithms. The concept can be used to some simple cases (Xu, Wan and Han, 1997).

9. Generalized Steady-State of Industrial Process

Actually from the point of view of steady-state optimisation the influence of stochastic noise in process variables is often ignored due to its low level and little influence to the objective function. The problem is called stochastic optimising control of steady-state systems, or the systems are under stochastic steady-state (Lin, Han, Roberts and Wan, 1989) if the noise can not be ignored.

Luo and Wan (1999a) have extended the concept of steady-state to a generalized form, *i.e.*, from the point of view of steady-state optimisation, a system may be under several kinds of steady-state that are constant, periodic, quasi-periodic, stochastic, chaotic steady- states in an industrial process or system. Actually some random process happens in a LSIP is often a mixture of the chaotic steady-state with a stochastic steady-state of low level. They have proposed a stringent definition about the generalized steady-state and proved that it exists when the nonlinear process satisfies some conditions. It is proved that the nominal central value of the generalized steady-state uniquely exists when the nonlinear process satisfies some conditions. The time averages of process variables uniformly converge to their respective nominal central values.

According to the definitions of generalized steady-state and the nominal central value of steady-state sets, Luo and Wan (1999a) stringently have described the problem of generalized steady-state optimizing control of industrial processes in a finite measure space. Under certain conditions above problem is transformed into a model based equivalent deterministic problem, and an algorithm for solving the problem has been suggested. A chemical process composed of a liquid level control system (LLCS) and a continuously stirred reactor (CSTR) (Fig. 6) has been used for simulation study of generalized steady-state optimizing control.

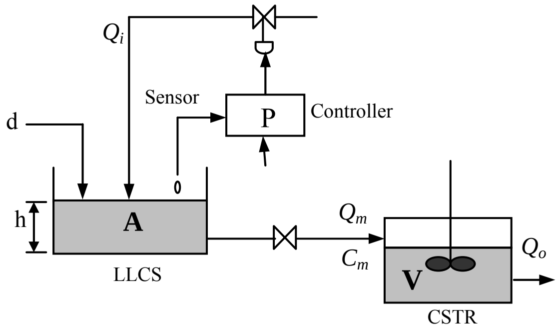

Figure 6. LLCS and CSTR

Luo, Han and Wan (1999) have stringently given a definition for the chaotic steady-state, and proved the existence theorem under some conditions. The chaotic steady-state of a chemical process is simulated. The steady-state modelling is based on an AFNI network (Luo, Liu and Wan, 1998). The global convergence of the steady-state generalized optimizing control algorithm has been proved based on Zangwill's Theorem of global convergence. Optimality of the optimizing control solution has been studied also (Luo and Wan, 1999b).

10. Global Convexification, Multi-Objective and Non-Separable Optimization Problems

Qian and Wan (2000) have proposed an approach through the p-th power transformation to obtain a global optimal solution by multi-objective optimization technique. The original optimization problem is embedded in a multi-objective optimization problem, then its non-inferior frontier is convexified. The original global optimal solution is picked up from the set of non-inferior solutions. Of course, this approach can be used to solve a multi-objective optimization problem for LSIP. Qian, Liu and Wan, (1999) has proposed a double iterative algorithm for non-separable multi-objective optimization problem which can satisfy the decision maker's preference.

For non-separable steady-state systems the Group has given an approaches for solving them. It is based on transversal transmission of information among local decision units to decouple the objective function,. Meanwhile the traditional longitudinal transmission of information is used to decouple the interconnection between subsystems (Qian and Wan, 1998a).

Another approach is for non-additive objective functions of general non-separable systems, Qian and Wan (1998b) have suggested a double-loop iterative algorithm. All these algorithms can be used for on-line optimizing control of LSIP.

11. Product Quality Control for Large–Scale Industrial Systems

A continuous casting and hot rolling production line in a Steel Complex in Shanghai is considered as a typical example (Fig.7). Knowledge Discovery in Database (KDD) is used to acquire data from computers of 3rd-generations for controlling the line, and from the computers in chemical analysis lab and material testing lab. To improve the product quality of the continuous casting and hot rolling, it is very necessary and important for a steel complex to find the relationship between the input variables and the product quality, i.e., to establish the steel plate static quality model. The steel plate quality model of a continuous casting furnace and hot rolling mill is a complex nonlinear function which after analysing and discussing with plant engineers Xing decides to include at least 32-input variables: 23 chemical elements variables for casting, 2 heating furnace variables, 7 rolling mill variables and 4-output variables (material testing indexes): rupture elongation rate, tensile strength, yield ratio and impact energy etc (Xing, 2000; Wan, 2002).

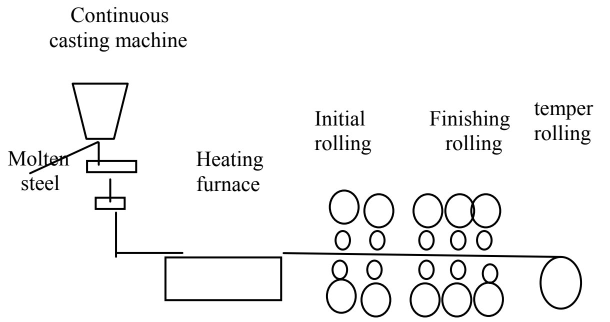

Figure 7. Continuous casting and hot rolling

All data used for modelling are preprocessed. 15, 000 useful sample data are obtained from 30, 000 and more observations in the data warehouse. Among them 9, 026 sample data are complete and can be used for modeling, however, they are corrupted by noise. And a high dimension input BP neural network is firstly chosen for the architecture of the steel plate quality model. To easily train and improve the accuracy the 32-input and 4-output BP neural network is decomposed as four 32-input and 1-output sub-neural network models. It is called the decomposition of the product quality modelling problem based on large-scale neural network.

The precision of modeling is expressed in the percentage of hits, i.e., the total number of hits in all 9, 026 data divided by 9, 026. A hit is defined as that pair of data which makes the model output within an error $\pm$ 5% of the real output.

Jia, Wan and Feng (2000) give a learning algorithm that each weight of BP neural network is trained separately with large inertia. The percentage of hits for suggested algorithm based on high- dimension -input BP neural network is 81.5%.

11.1 Modelling Based on Wavelet Neural Network

It is important to notice that the sequence of real output is in a saw tooth-like form . For this reason the wavelet neural network (WNN) is a better choice for the modelling problem.

Li and Wan (2002) choose the similar structure of the WNN as that of multi-layer perceptron (MLP), except that here the activation function of hidden nodes is replaced by a B-spline wavelet function of one dimension. Employing the MLP-like architecture, the proposed three layer WNN (1-input, 1-hidden layer and 1-output) is a powerful tool to handle high dimensional problem. The percentage of hits for this quality model is 81.5%, while that for an ordinary BP three layer neural network with the same number of nodes provides a precision 62.7%.

11.2 High-Dimension-Input Wavelet Neural Network Based on Work Procedure of the Technology and Key Inputs

The production line is a serially connected system and 32 input variables start act at different stages according to the work procedure. Therefore Li and Wan (2004a) suggest a WNN with several input layer depending on the work procedure (Fig.8). For instance, in first input layer there are 22 input variables (chemical-element variables) simulating the casting, in second input layer there are 2 variables simulating the heat furnace, and in the third layer there are 7 variables simulating the rolling. And for this special kind of steel plate there are three most important chemical elements, viz., carbon, manganese and titanium. Their corresponding input variables are connected to the input as well as the output nodes directly. A suitable learning algorithm is given also. The percentage of hits for quality model of this architecture is 93.4%.

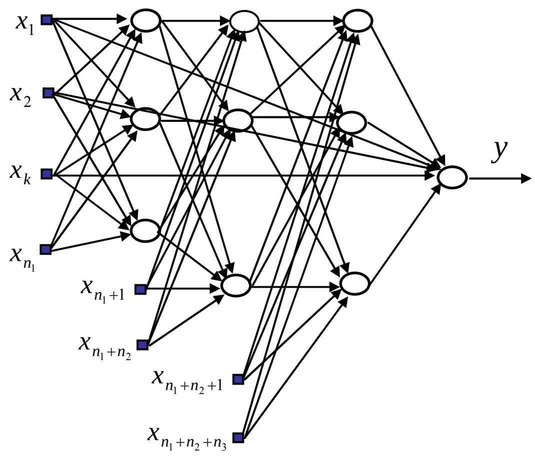

Figure 8. The architecture of three-input-layer wavelet neural network based on work procedure and key inputs
■ - Input node; ○ - Neuron

The further improvement of the precision can be made by clustering all the data and dividing them into 12 groups, and using the modular WNN approach (Li 2003). Then each submodel gives a precision about from 93.4~95% depending on the group of data used in modeling. And using a filled function algorithm to get a global optimum makes the above WNN result further improve 1% of precision (Li and Wan, 2004b; 2004c).

11.3 Application of Product Quality Model to New Product and New Technology Design

More occasionally it is not allowed to change all the manipulating variables in a quality model. Therefore, a new kind model, product quality control model, is suggested in which the input variables are quality index and those variables that are not allowed to change or that are assigned preliminary, and the output variables are some manipulating variables that are allowed to change. By the latter one can find the manipulating variables required from the quality index value (Xing, 2000). For instance, for a certain kind of titanium-manganese alloy steel plate the manipulating variables required or engineers hope to get from the quality control model are the amount of titanium, manganese and carbon. Sometimes the quality control model is more convenient in practice.

manipulating variables from these four submodels is a serious problem for the continuous casting and hot rolling. It is called the coordination or synthesis of the product quality modelling problem based on large-scale neural network. For simple cases the solution is the intersection set of the output manipulating variable sets from the quality control submodels. But in more complicated cases, perhaps, some kind of data fusion is necessary. How to overcome this drawback needs further study. And evidently it needs different kinds of such quality models for different design purposes.

12. Conclusions

The paper concludes that the second stage steady-state hierarchical optimization has extended to generalized steady-state hierarchical optimization and that the third stage ISOPE has extended to ISOPE and DISOPE (dynamic integrated system optimization and parameter estimation) stage, and that the fourth stage is the hierarchical intelligent control and optimization stage. Obviously, the latter is a very important one.

In the Group's experience the neural network modelling using the data from normal set-point changes, updated by newly coming data, the optimization algorithm selected from different intelligent methods depending upon the nature of the problem, application of iterative learning control technique, and integrated with fault diagnosis is a good choice, it gives great potential for increasing profit. And all these functions can be integrated in intelligent agents for on-line steady-state intelligent hierarchical control of LSIP.

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REFERENCES

1. CHEN, Q-X and B-W WAN, **Asymptotic Normality Analysis of the Estimation Error of Steady-State Models for Industrial Processes: SISO Case**, Int.J. Systems Sci., Vol. 23, No.11, 1992, pp. 2003-2023.

2. CHEN, Q-X and B-W WAN, **Steady-State Identification for Large-Scale Industrial Process by Means of Dynamic Models**, Int. J. Systems Sci., Vol. 25, No. 5, 1995, pp. 1079-1101.

3. CHEN, Q-X and B-W WAN, **A New Approach to Establish a Steady-State Model of an Industrial Process**, Int. J. Systems Sci., Vol. 30, No. 10, 1999, pp. 1073-1091.

4. GU, JIA-CHEN and BAI-WU WAN, **Interaction Balance Method for Large-Scale Industrial Processes with Fuzzy Parameters**, Acta Automatica Sinic, Vol. 28, No. 4, 2002, pp. 569-574, (in Chinese).

5. GU, JIA-CHEN and BAI-WU WAN, **Interaction Prediction Method for Large-Scale Industrial Processes with Fuzzy Parameters**, Control and Decision, Vol. 16, No. 1, 2001, pp. 58-61 (in Chinese).

6. GU, JIA-CHEN and BAI-WU WAN, **Mixed Coordination Method for Large-Scale Industrial Processes with Fuzzy Parameters**, Control Theory and Applications, Vol. 19, No. 5, 2002, pp. 763-770 (in Chinese).

7. HUANG, Z-L and B-W WAN, **Identification of Steady-State Model for Nonlinear System Described by Volterra Series and Its Strong Consistency**, Journal of Xi'an Jiaotong University, Vol. 31, No. 6, 1997, 20-26 (in Chinese).

8. HUANG, Z-L, B-W WAN and C-Z HAN, **A New Approach to Estimate the Process Derivative and Its Strong Consistency Analysis**, Control Theory and Applications, Vol. 11, No. 1, 1994, pp. 12-19 (in Chinese).

9. JIAO, B-C, C.W. LI and B-W WAN, **A Convexifying Approach to Separable Non-Convex Large-Scale Steady-State Systems**, Preprint of IFAC/IFORC/IMAC Symposium on Large-scale Systems Theory and Applications, Vol. 1, 11-13, July, 1995, London, U.K., pp. 117-122.

10. LEUNG, T-P, Y-J LI and B-W WAN, **Static Hierarchical Optimization of Large-Scale Systems Based on Hopfield Network**, Proceedings of the 1-st Chinese World Congress on Intelligent Control and Intelligent Automation, Vol. 1, Beijing, China, Aug. 26-30, 1993, pp. 556-559 (in Chinese).

11. LI, HUAN-QIN and BAI-WU WAN, **Product Quality Model Based on High Dimension Input Wavelet Neural Network for Hot Rolling Mill**, Proceedings of the 2002 International Conference on Control and Automation, 16-19 June, 2002, Xiamen, China, pp. 60-63.

12. LI, HUAN-QIN and BAI-WU WAN, **Multi-input layer Wavelet Neural Network and Its Application**, Acta Automatica Sinica, Vol. 30, No. 4, 2004, pp. 939-943 (in Chinese).

13. LI, HUAN-QIN and BAI-WU WAN, **A Wavelet Neural Network Model for Industrial Product Quality Based on the Filled Function Algorithm**, Acta Automatica Sinica, Vol. 30, No. 2, 2004, pp. 283-287 (in Chinese).

14. LI, HUAN-QIN and BAI-WU WAN, **Using Multi-input layer Wavelet Neural Network to Model Product Quality of Continuous Casting Furnace and Hot Rolling Mill**, Journal of Systems and Information, 2004, 2(2), pp. 309-317.

15. LI, L-Z, S-Y QIN and B-W-WAN, **Intelligent Interaction Prediction Method for Multi-Objective Optimization of Large-Scale Steady-State Systems**, Preprint of IFAC Symposium of large-scale Systems Theory and Application, August 23-25, 1991, Beijing, China, Vol. 1, pp. 228-233.

16. LI, L-Z, S-Y QIN and B-W WAN, **Intelligent Coordination Method with Objective-Modified for Large-Scale Steady-State Systems**, Proceedings of IEEE International Conference on Intelligent Control and Instrumentation, Vol. 1, February 1992, Singapore, pp. 157-161.

17. LI, L-Z, S-Y QIN and B-W WAN, **Intelligent Optimization Method for Large-Scale Steady-State Systems with Fuzzy Parameters**, Proceeding of IEEE International Conference on System, Man, and Cybernetics, October 18-21, Chicago, Illinois, 1992, Vol. 2, pp. 1283-1288.

18. LI, Y-J, B-W WAN and T-P LEUNG, **Steady-State Optimizing Control for Large-Scale Systems with Hopfield Network**, Proceeding of First Asian Control Conference, Tokyo, Japan, July 27-30, 1994, Japan, Vol. 3, pp. 559-562.

19. LI, Y-J, B-W WAN and T-P LEUNG, **Steady-state optimizing control using dynamic information for large-scale industrial processes with Hopfield network**, Preprint of IFAC/IFORC/IMAC Symposium on Large-scale Systems Theory and Applications, Vol. 1, 11-13 July, 1995, London, U.K., pp. 129-134.

20. LIU, DING and BAI-WU WAN, **Model Identification and Steady-State Optimizing Control of Wind System for Air Preheater,** Acta Automatica Sinica, Vol. 25, No. 6, 1999, pp. 728-734 (in Chinese).

21. LUO, X-G and B-W WAN, **A Study on the Optimizing Control of General Steady-State for Industrial Processes**, Chinese Journal of Automation (Allerton Press, Inc.), Vol. 11, No. 3, 2000, pp. 213-220.

22. LUO, X-G and B-W WAN, **Research on the Convergence of Generalized Steady-State Optimizing Control Algorithm for Industrial Processes**, Acta Automatica Sinica, Vol. 26, No. 3, 2000, pp. 382-386 (in Chinese).

23. LUO, X-G, D. Liu and B-W WAN, **An Adaptive Fuzzy Neural Inferring Network**, Fuzzy Systems and Mathematics, Vol. 12, No. 4, 1998, pp. 26-33 (in Chinese).

24. QIAN, FU-CAI and BAI-WU WAN, **Improvement of Interaction Balance Method of Coordination for Steady-State Large-Scale Systems**, Systems Engineering Theory and Practice, Vol. 18, No. 8, 1998a, pp. 87-90 (in Chinese).

25. QIAN, FU-CAI and BAI-WU WAN, **Hierarchical Optimizing Control for Non-Separable Steady-State Large-Scale Systems**, Journal of Xi'an Jiaotong University, Vol. 32, No. 7, 1998b, pp. 21-28 (in Chinese).

26. QIAN, FU-CAI, DING LIU and BAI-WU WAN, **Double Iterative Hierarchical Algorithm for Multi-Objective Optimization of Steady-State Large-Scale Systems**, Journal of Applied Sciences, Vol. 17, No. 4, 1999, pp. 479-484 (in Chinese).

27. QIAN, FU-CAI and BAI-WU WAN, **Global Optimization and Hierarchical Control of Separable Nonconvex Large Scale Steady-State Systems**, Journal of Xi'an Jiaotong University, Vol. 34, No. 12, 2000, pp. 44-46 (in Chinese).

28. ROBERTS, P. D., B-W WAN and J. LIN, **Steady-State Hierarchical Control of Large-Scale Industrial Processes: A Survey**, Preprint of IFAC Symposium on large-scale Systems Theory and Application, 23-25 August, 1991, Beijing, Vol. 1, pp. 1-10.

29. RUAN, XIAO-E, BAI-WU WAN and HONG-XIA GAO, **The Iterative Learning Control for Saturated Nonlinear Control Systems with Dead Zone**, Proc. of the 3-rd Asian Control Conference, 4-7 July, Shanghai, China, 2000, pp. 1554-1557.

30. RUAN, XIAO-E, BAIWU WAN, FENGMIN CHEN, **Decentralized Iterative Learning Controllers for Nonlinear Large-Scale Systems to Track Trajectories with Different Magnitudes**, Acta Automatica Sinica (Accepted in Nov. 29, 2007).

31. RUAN, X-E, Z. BIEN and K.-H. PARK, **Iterative Learning Controllers for Discrete-Time Large-Scale Systems to Track Trajectories with Distinct Magnitudes**, International Journal of Systems Science, Vol. 36, No. 4, 2005, pp. 221-233.

32. RUAN, XIAO-E, Z. ZENN BIEN, KWANG-HYUN PARK, **Decentralized Iterative Learning Control to Large-Scale Industrial Processes for Nonrepetitive Trajectory Tracking**, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 38, No. 1, Jan. 2008, pp. 238-252.

33. RUAN, XIAO-E, HUAN-QIN LI, BAIWU WAN, **The Local-symmetrical-double-integral Type Iterative Learning Control for Dynamics of Industrial Processes with Time Delay in Steady-State Optimization**, Acta Automatica Sinica, Jan. 2003, Vol. 29, No. 1, pp. 125-129 (in Chinese).

34. WAN, BAI-WU, **Product Quality Model and Quality Control Model for Industrial Production and their Applications**, Acta Automatica Sinic, Vol. 28, No. 6, 2002, pp. 1019-1024 (in Chinese).

35. WAN, BAI-WU and ZHENG-LIANG HUANG, **On-line Steady-state Hierarchical Optimizing Control of Large-scale Industrial Processes**, Science Press, Beijing, China, 1998 (in Chinese).

36. WAN, W-H, B-W WAN and J-Y YUAN, **Neural Network Modelling and Steady-State Optimizing Control for Nickel Flash Furnace in Smelting Plant**, Preprint of 14-th World Congress of IFAC, Beijing, China, Vol. N, 1999.7, pp. 415-420.

37. WANG, W-Y and BAI-WU WAN, **Neural Network Identification of Steady-State Process Model Using Dynamic Data**, Proceedings of Symposium on Control, Automation Applications (CAI'93), Hong Kong, March 3, 1993, pp. 16-24.

38. WANG, W-Y, B-W WAN and B, SONG, **Steady-State Hierarchical Stochastic Optimizing Control of A Mixer Pilot Plant Based on Neural Network Modelling**, Proceedings of the 7-th CAA/CACE Science Conference on Process Control, Vol. 1, Qingdao, China, 1994, pp. 5-25 (in Chinese).

39. XING, JIN-SHENG, **An Investigation on Steel Plate Quality Model of Large-Scale Hot Rolling Mill Using KDD Technology**. [Ph.D. Thesis]. Xi'an Jiaotong University, Xi'an, China (in Chinese).

40. XU, L-J and B-W WAN, **Robustness of Optimizing Control Algorithms for Steady-State Industrial Process**, Proceeding of First Asian Control Conference, Tokyo, Japan, July 27-30, 1994, Vol. II, pp. 537-540.

41. XU, L-J, B-W WAN and C-Z HAN, **Robust Stability and Improved Scheme of Optimizing Control Algorithm for Steady State Industrial Processes**, Proceedings of the 2nd Chinese World Congress on Intelligent Control and Intelligent Automation, Vol. II, July 23-27, 1997, Xi'an, China pp. 1190-1194.