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Osamu Iida, Shuichi Taniyoshi, Toshio Uetani, Toshiro Sawada, Masahiro Hashimoto, Daisuke Onoda

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The No. 3 blast furnace of Mizushima Works applies artificial intelligence (AI) techniques in its thoroughly re-modernized plant control system. AI has been applied in the blast furnace operation to diagnose the blast furnace condition and control furnace heat (a diagnosis type of expert system), to control hot stove heat by fuzzy theory, to plan the material hopper arrangement (a planning type of expert system), to control the distribution of granulated slag (a control type of expert system in real-time), and to control the feed speed of material by fuzzy theory. These functions have greatly contributed to a high degree of automation and efficient operation of the furnace.

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Osamu Iida
Staff Deputy Manager, Plant Control Technology Sec., Plant Control Technology Dept., Mizushima Works

Shuichi Taniyoshi
Staff Deputy Manager, Plant Control Technology Sec., Plant Control Technology Dept., Mizushima Works

Toshio Uetani
Staff Deputy Manager, Ironmaking Sec., Ironmaking Dept., Mizushima Works



Toshiro Sawada
Staff Deputy Manager, Ironmaking Sec., Ironmaking Dept., Mizushima Works

Masahiro Hashimoto
Assistant Manager, Raw Materials Processing Sec., Production Control Dept., Kawatetsu Mining Co., Ltd.

Daisuke Onoda
Plant Control Technology Sec., Plant Control Technology Dept., Mizushima Works

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1 Introduction

At the first stages of application of artificial intelligence (AI) to industrial fields, the ironmaking division of Mizushima Works at Kawasaki Steel had insight into its great potential. The division has ever since been seeking its application to solve various problems, and several of these applications have already been put to practical use with significant success, such as the blast furnace operation control system (a diagnosis type of expert system)[1-4] and the coal blending plan (a planning type of expert system).[5]

The No. 3 blast furnace of Mizushima Works was blown in for the third time in June 1990, and the AI technique was applied to various aspects of its operation, using experience of AI applications up to that time. This paper reports the AI techniques which have been applied to the blast furnaces at Kawasaki Steel, with particular emphasis on those applied to the No. 3 blast furnace at Mizushima Works.

2 Features of Blast Furnace Operation and Usefulness of AI Techniques

A blast furnace is a device that reduces and melts iron ore to produce pig iron, and consists of the furnace itself and multiple support facilities shown in **Fig. 1**.

Blast furnace operation to produce pig iron from iron ore and coke is a very complex reaction behavior in-

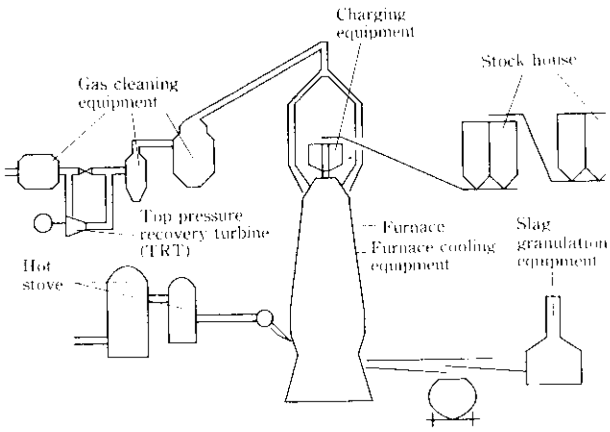

Fig. 1 Schematic diagram of blast furnace

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volging three kinds of forms (liquid, solid and vapor) of materials, being very difficult to describe in any theoretical expression, and consequently to construct a process model. Therefore, blast furnace operation has become usually dependent on the operators' experience, and the application of a physical model or process control model based on control theory has been neglected.

However, the progress of AI techniques in recent years has indicated their suitability for blast furnace application, and the use of such AI techniques as the expert system and fuzzy theory has been attempted. Several systems employing AI techniques have been developed at Kawasaki Steel, starting with the development of a blast furnace control system in 1988, and the usefulness of AI techniques has been confirmed for this.

This experience was used as the basis for the third revamping to No. 3 blast furnace at Mizushima Works, in which an updated operation control system was applied to the maximum in order to upgrade the level of the existing AI system. The application of AI techniques was expanded to solve the problems of planning and real-time control, thereby attempting further automation and improvement of blast furnace operation.

3 Configuration of the No. 3 Blast Furnace Operation Control System

The configuration of the operation control system for No. 3 blast furnace is shown in **Fig. 2**. This system has a three-hierarchy configuration comprising the electrical and instrumentation controller (PLC and DCS), process computer and central computer to completely unify the aspects of electrical and instrumentation control (EI unification). Functions to which the AI technique such as the expert system and fuzzy control is applied are achieved by the process computer and the exclusive-use microcomputer, which constitutes part of the PLC system, and the functions properly select the hardware to be used and the AI tool to be used according to the object and the purpose to which the AI technique is to be applied.

4 Application of AI Techniques to Blast Furnace Operation

The No. 3 blast furnace at Mizushima Works applies AI techniques to blast furnace control (a diagnosis type of expert system), to material hopper planning (a planning type of expert system), to distribution control of the granulated slag (a real-time control type of expert system), and to hot stove heat control and distribution control of charged materials (for which fuzzy inference is used).

4.1 Blast Furnace Control System

The blast furnace control system diagnoses the operating condition of the blast furnace from a multitude of process information and gives guidance to the operator about necessary operating actions together with the results of the diagnosis.

The functions of the blast furnace control system are to estimate and diagnose the phenomena existing inside the blast furnace from a large quantity of measured data (amounting to 250 data items in total in the case of No. 3 blast furnace) and numerous indices, and to determine the method and degree of appropriate actions to be taken to match the phenomena. These phenomena inside the blast furnace include those changing with a large time constant (such as the thermal conditions of furnace heat and pig balance) and those changing more rapidly (such as abrupt fluctuations in blast pressure). To handle both, the knowledge base for diagnosing is divided, as shown in **Fig. 3**, into two sections: the stationary knowledge base for performing a cyclic diagnosis when

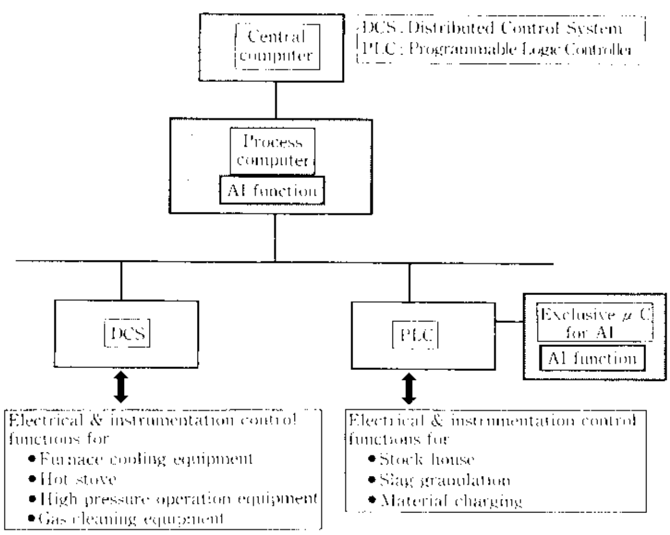

Fig. 2 Configuration of the control system for No. 3 blast furnace

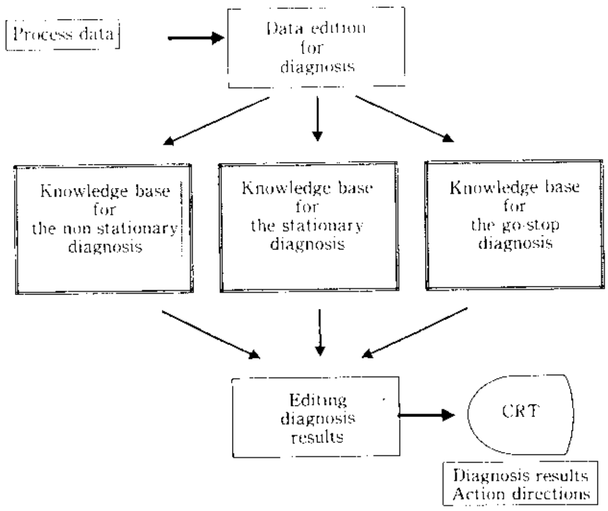

Fig. 3 Configuration of knowledge base in the blast furnace expert system

Table 1 Scale of the knowledge base

Name	Number of production rules	Number of knowledge frames	Execution timming
Knowledge base for the stationary diagnosis	508	50	Every 5 min, 15 min, and 1 day (different from rule groups)
Knowledge base for the non stationary diagnosis	50	5	Executed by events
Knowledge base for the go-stop diagnosis	37	1	Every 15 min

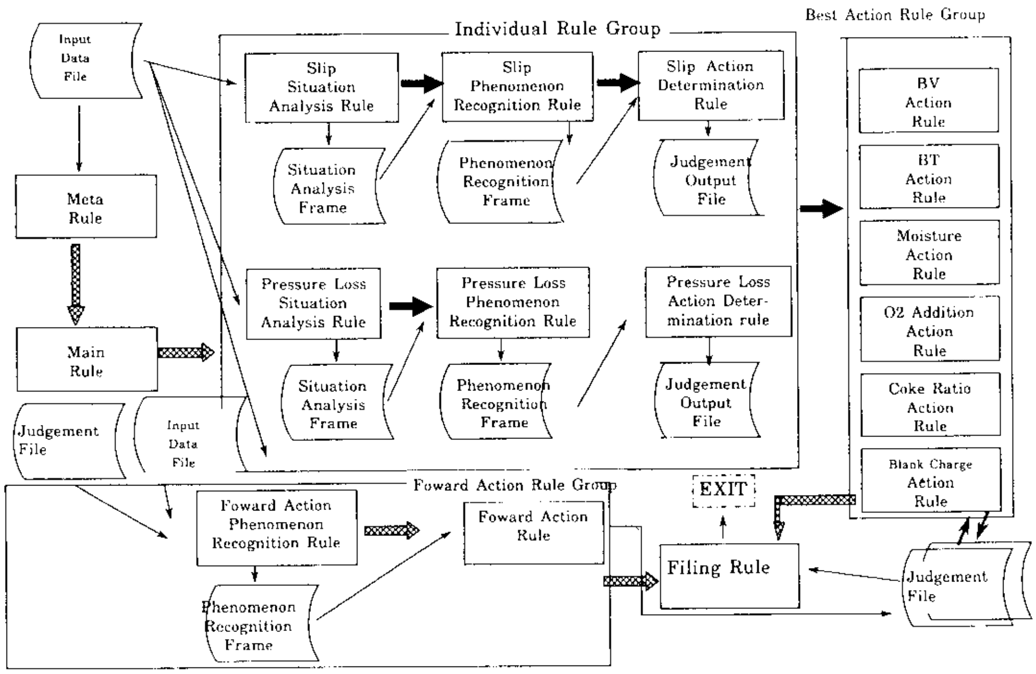

Fig. 4 Configuration of the rule groups

slow change happens, and the non-stationary knowledge base for event driven diagnosis when rapid change happens. In the stationary knowledge base, knowledge is described in the form of production rules, and the stationary knowledge base is divided into 23 kinds of individual rule groups corresponding to phenomena to be diagnosed, as shown in **Fig. 4**. Diagnosed results derived from the rule group corresponding to these individual phenomena are given a final judgement by the "best action determining group" and "forward action determining group", thereby providing suitable instructions to the operator as guidance. The actions involved in this system are the blast volume, blast temperature, blast moisture, coke ratio, O_2 environment volume, and blank charge (charging coke only). Transfer of knowledge between rule groups is carried out by means of knowledge frames. The scale of the knowledge base is shown in **Table 1**.

The output from the knowledge base is displayed to the operator as guidance on a CRT screen and by voice annunciator, both the result of the inference and the reason for the result being explained. This explanation

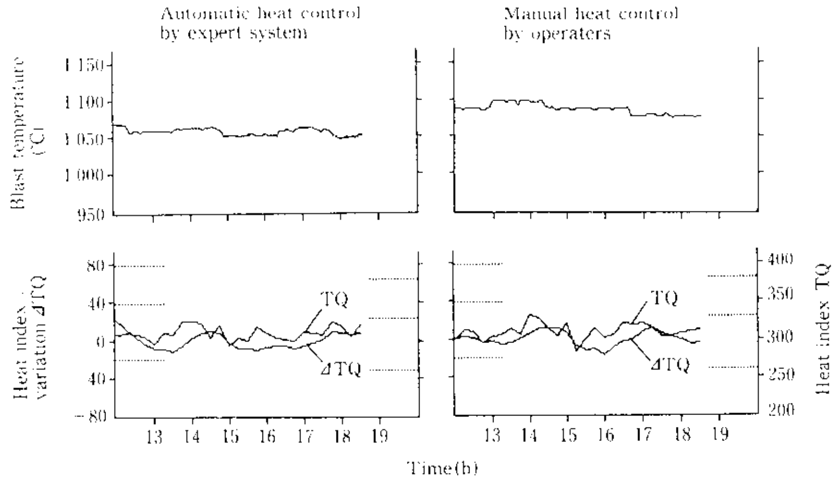

Fig. 5 Results of the automatic blast furnace heat control

is provided by tracing back to the rule that was used to obtain the result.

The system for No. 3 blast furnace includes the "Go-Stop knowledge base," which corresponds to the conventional Go-Stop system and provides an emergency refuge, thereby giving the required degree of control when the blast furnace condition suddenly changes.

With a conventional type of guidance diagnosis system, the operator interprets the output of the system and makes a judgement as to whether or not action should be taken according to the instruction. In the system for No. 3 blast furnace, however, the blast temperature action for farnace heat control is automatically taken without the operator's judgement. **Figure 5** shows a comparison between the expert system and manual operation in terms of automatic furnace heat control. Fluctuation of the furnace heat index (TQ), which indicates the furnace heat conditions, is no less inferior to the case of manual operation by operators, proving a sufficient functioning of the furnace heat automatic control by this system.

4.2 Hot Stove Combustion Control System

The hot stove, as shown in **Fig. 6**, is a very large batch type of heat exchanger, and generates the hot blast for the blast furnace. The purpose of hot stove combustion control lies in supplying blast furnace with a hot blast of the prescribed temperature and the highest thermal efficiency, and also in maintaining the temperature of the refractory bricks of the hot stove within a certain temperature range for optimum durability. Operating conditions which satisfy such demands can be theoretically obtained by calculating in-and-out heat quantities. In reality, however, process data that indicate the characteristics of a hot stove such as the blast volume passing through cannot be accurately measured, and the consequent difficulty in correctly defining the operating condition prevents a model from producing

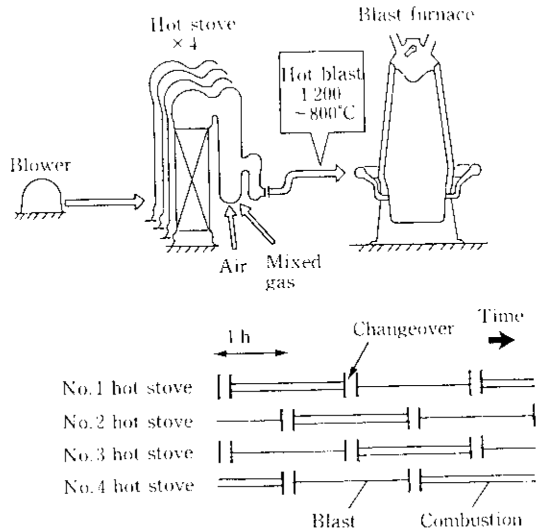

Fig. 6 Outline of hot stoves

satisfactory results. In contrast, a skilled operator can provide satisfactory control by inferring the heat condition of the hot stove from certain process data. In analogy, a control model that expresses the know-how of an operator by a type of fuzzy rule has recently been applied, instead of a physical model, to No. 6 blast furnace at Chiba Works, as well as to several other blast furnaces.[6, 7]

The hot stove combustion control system that is used for No. 3 blast furnace is a hybrid type consisting of a physical model applying the heat balance calculation, and an expert system applying fuzzy inference, as shown in **Fig. 7**.

The physical model is activated when the blast volume and blast temperature change significantly. The optimum new operating conditions for the hot stove are then calculated to provide the highest thermal efficiency and lowest operating cost.

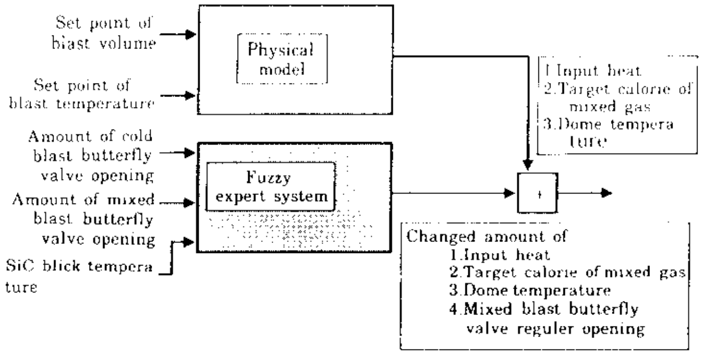

Fig. 7 Configuration of the hot stove heat control

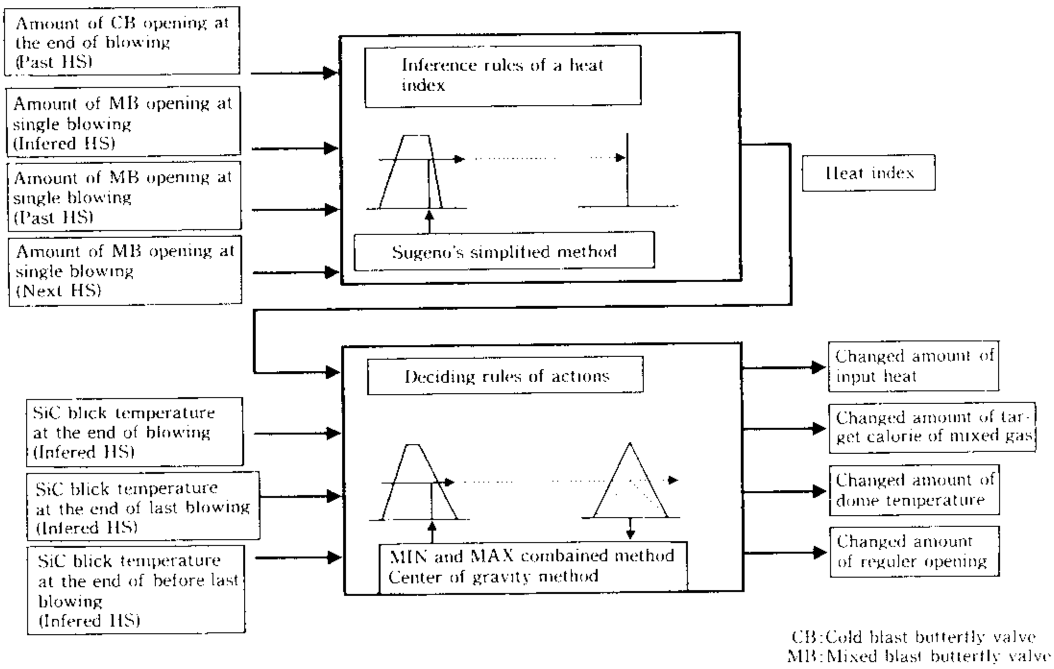

Fig. 8 Configuration of the fuzzy rule groups

If the characteristics of the hot stove are the same as those represented by the physical model, operations according to the conditions obtained from the physical model should achieve the best result. In practice, however, the operating conditions are changed. The control model using fuzzy inference is then activated to meet these unplanned situations before the stove commences combustion after completing blasting, and checks the heat condition of the stove and the brick temperature, thereby correcting control parameters to maintain the most suitable operating conditions.

The configuration of the fuzzy rules in the present control model is shown in **Fig. 8**. In the first-stage fuzzy group, an index is obtained that evaluates the heating condition of the stove (the heat index), using as inputs, (1) the opening of the mixed blast butterfly valve when single blowing of the hot stove occurs at change-over, and (2) the opening of the cold blast butterfly valve just before blasting ends. For valve opening, the heating states of two stoves are shown in a synthesized shape, but since the present rule group is required to judge the heating condition of a single stove, four items of information about valve opening are input to form a rule that can infer the heating condition of the stove being considered.

In the second-stage fuzzy rule group, the following inputs are used: (1) the heat index obtained by the first-stage inference, (2) the brick temperature of the object stove at the end of blowing, and (3) the change of brick temperature during times of cycles in the past. The required adjustment to the control parameters is then obtained by fuzzy inference. The output from this rule group are: (1) the change of input heat (2) the target calorific value of the mixed gas, (3) the dome tempera-

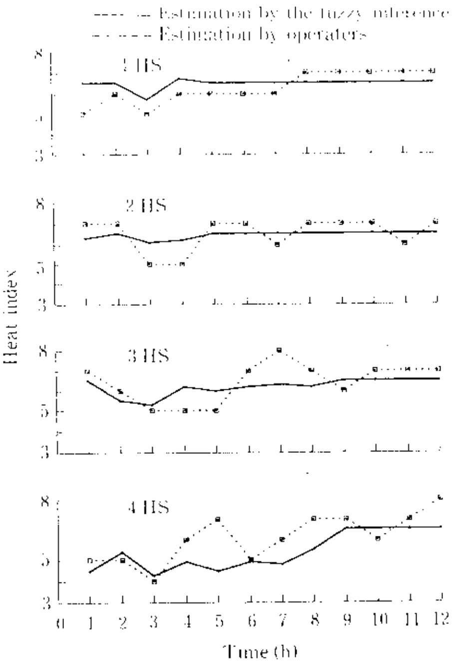

Fig. 9 Estimation of the fuzzy inference

ture, and (4) the change of opening of the mixed blast butterfly valve at the time of two stoves blowing.

Figure 9 shows a comparison between the heat index obtained by the fuzzy rule, and evaluation by an operator. Agreement is good, indicating that the rule fully reflects the concerned know-how.

4.3 Material Hopper Planning

The raw materials to be charged into the blast furnace involve several tens in kind varying in ingredient and grain size. These materials are stored in stock bins adjacent to the blast furnace, and after being weighed by scales installed below the storage hoppers, are charged into the blast furnace. In the case of No. 3 blast furnace, two lines of stock bins, each consisting of 10 hoppers, are provided as shown in **Fig. 10**, and the weighing capacity of each scale is different. Iron ore is charged into the hopper by the shuttle-reverse conveyor installed at the top of the hopper.

Planning the hopper material involves determining what a hopper should store by brand of iron ore on the basis of the charging instruction given to the blast furnace regarding the brand and weight at each charging. This must be done without exceeding the weighing capacity and charging limit of the respective hopper to feed a designated quantity of iron ore. In the past, this was determined by the judgement of an operator, but since the installation of an iron ore classifier, the number of variables to be taken into consideration have increased. Therefore, a process computer is used for automatic planning. As a planning problem, this problem is a comparaively simple one, and it was possible to

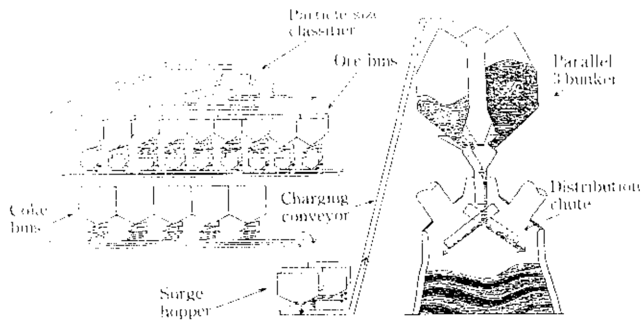

Fig. 10 Process flow of material charge

Table 2 Comparison of the productibity to make "the planning of material hopper arrangement" by use of expert shell and procedure-oriented language

Language	Process computer	Central computer
	Expert shell (AIMAX-C)	COBOL
Number of program steps	4 612	5 124
Productibity (step/man-month)	1 749	557

construct functions by a procedure oriented language, although the expert shell used in the blast furnace control system was employed in its construction because of its ease of use. However, exactly the same functions are described by COBOL in the central computer, and **Table 2** shows a comparison between the two systems. This shell program proved to be far better in software productivity, and clearly shows that this expert shell is a tool that can improve software productivity in the case of specific problems.

This function is started in batches on the basis of charging instructions transmitted by the central computer, thereby automatically forming the material hopper plan. The operator intercedes only in special cases, and formulation.

4.4 Distribution Control of Granulated Slag

The slag granulation process is an auxiliary facility of the blast furnace for producing granulated slag as a by-product of pig iron. In this process, molten slag separated from the hot metal is granulated and rapidly cooled by pressurized water, before being blown into the stirring tank and turned into granulated slag. This granulated slag is transported as a slurry and is selectively charged into the dehydration tank. At the same time, a quality judgement of the slag in terms of color and amount of mixed iron skull is carried out on-line by automatic quality assessment equipment. Subsequently the granulated slag is suspended for a certain time by a

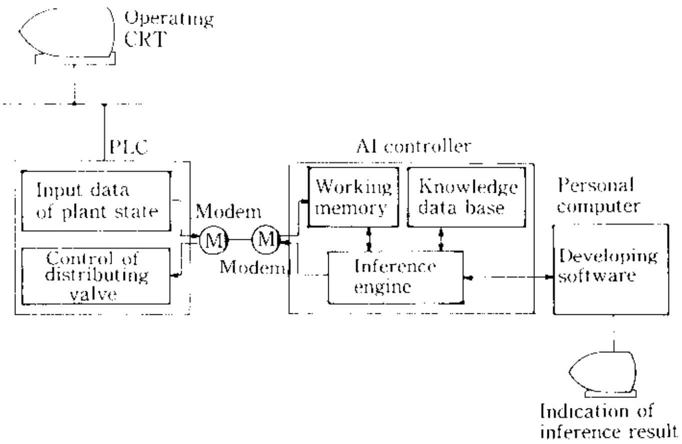

Fig. 11 Function block diagram

screen at the bottom of the dehydration tank, before being filtered and dehydrated, and is finally loaded through the discharge valve into the exclusive-use dump cars for transportation to the delivery yard.

The stage that requires the most important judgment in this process is the selective charging of the dehydration tank. It is necessary to give instantaneous judgment on the properties of both the charging and the receiving sides of the granulated slag so as to achieve efficient operation of the dehydration basin and ensure suitable quality of the granulated slag. The charging side properties include transition prediction for the quantity, time and quality of the molten slag, and the receiving side properties include a multitude of information such as the conditions in the dehydration basin, dehydration prediction, discharge, production quality, quantity of granulated slag and water, water balance, tap data, operation control conditions, distribution valve opening, and the conditions for the tapping speed calculation.

To handle this, a real-time control and event-driven expert system was developed for dehydration basin distribution control. This system ensures efficient blast furnace operation and granulated slag quality, as well as one-man blast furnace operation.

The configuration of the system is shown in **Fig. 11**, and comprises PLC to provide the intrinsic control of the granulation system, an exclusive AI controller, a personal computer for software development, and a high-speed serial transmission device to connect all these units. PLC exclusively carries out high-speed automatic control by the fixed sequence and PID method based on control-driven programming language, and outside this loop, there is an AI controller which forms a pliable loop for recognition⟶inference⟶execution. Information which becomes the base from recognition and excusion is connected to PLC by a high-speed transmission device. This configuration provides the required real-time control, as well as flexibility in operating the system and a reduction in the development time scale.

4.5 Control of Hopper Discharge Rate

The material charging process is a handling facility which supplies raw material particles such as iron ore and coke to the blast furnace. The vital control elements are brand, schedule, time, position and rate required to supply these raw materials stably and correctly to the blast furnace. A flow chart of this process is shown in Fig. 10. During the third relining, a new bell-less system to allow charging by particle size, and parallel furnace-top bunkers were introduced to control the segregation of particles.

To achieve this, fuzzy control was applied to three locations, involving unloading from the ore bin, discharging from the surge hopper and charging from the furnace-top bunker. A control target common to all three is the discharge speed, which is controlled only by the gate opening. The discharge speed and gate opening form a tentative linear relationship, but such other parameters as brand, individual characteristics of each bin, material grain size, moisture and material weight affect each other in a complex manner that is not time-based. A feed-forward method involving the grain size and moisture value is also conceivable, but the sensing technique for this remains to be developed. In the past, the operator used a table of discharge rate and gate opening to make microadjustments by relying on experience and skill.

The configuration of the fuzzy grain control system that was introduced is shown in **Fig. 12**. In Fig. 12, fuzzy control is applied to unloading from the ore bin, and the control rule $Y_i = f_i(X_i)(i = 1, 2, \ldots n)$ that the skilled operator used is applied to adjust the gate opening by fuzzy inference and feed-back. The fuzzy variables involved in this are the gate opening, actual discharge rate and from the predicted rate deviation.

This grain control method uses fuzzy logic to achieve real-time and high-speed operation by PLC, using a

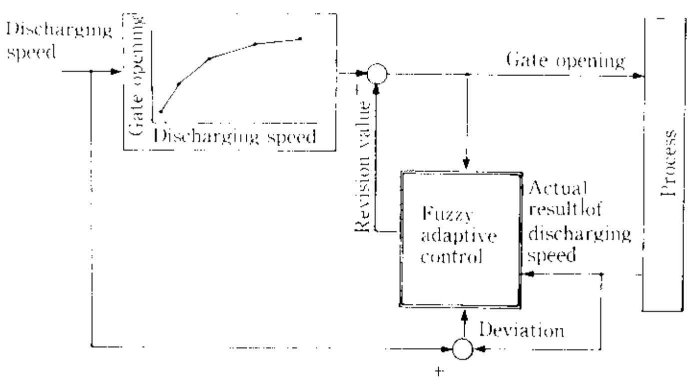

Fig. 12 System block diagram of fuzzy control for grains (adaptive control for revision value of gate opening)

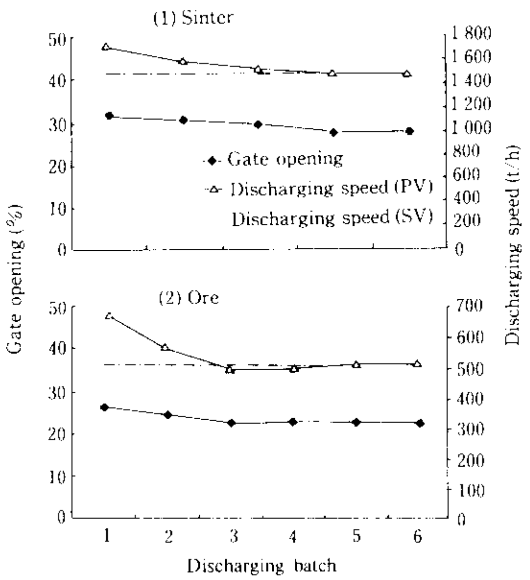

Fig. 13 Results of discharging speed control

simplified membership function. Consequently, the sequential control inherent to PLC and the logic type of "IF-THEN" control algorithm are used in parallel.

A comparison between this control method and conventional control is shown in **Fig. 13**. This shows an example of unloading control from the ore bin, and a much faster response is apparent than was possible by the operator making manual micro-adjustments.

5 Conclusions

AI techniques were applied to controlling the No. 3 blast furnace operations at Mizushima Works.

(1) Blast furnace control is by a diagnostic type of expert system, and gives guidance to the actions required for blast furnace operation, as well as control of the furnace heat by automatically setting the blast temperature.

(2) Hot stove combustion control is by a combination of fuzzy inference and a physical model to ensure good thermal efficiency of the hot stove and to protect the refractory bricks.

(3) Hopper material planning is done by a planning type of expert system at the process computer level.

(4) Granulated slag distribution is controlled by an expert system operating real-time, and has enabled complete automation of the granulating process.

(5) Hoppers discharge rate is controlled by uses fuzzy inference to eliminate the segregation of material brands during raw material discharging.

Experience of AI to control the blast furnace and other iron-making operations has proved its capability for achieving automation and increased operating effiency, its value being very high. For this reason, the applications of AI techniques will be extended in the future, and such new techniques as the neural network will be studied to further improve the power of AI.

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