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Artificial Intelligence Applications at Kawasaki Steel

Junjiro Yamasaki, Tadaaki Iwamura

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The body can be viewed from the next page.

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Junjiro Yamasaki
Staff Assistant General Manager, Plant Control Technology Sec., Plant Control Technology Dept., Mizushima Works

Tadaaki Iwamura
Chief of Plant Control Technology Sec., Plant Control Technology Dept., Mizushima Works

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1 Introduction

In the steel industry, artificial intelligence (AI) technology has emerged from the trial period and entered the stage of practical application. As a theoretical system, AI is a comprehensive term covering knowledge engineering, fuzzy logic, and neuro-network theory. Progress in the application of AI has kept pace with the remarkable development of computer technology, and now includes a number of examples in the steel industry.

As an early example of the trend in the steel industry, Kawasaki Steel Corp. adopted knowledge engineering techniques at its round billet conditioning yard in February 1984. This was not a conventional batch-based consulting-type knowledge engineering system, but was the world's first application of a real-time expert system to a commercial process of this type. Since that time, AI techniques have been aggressively adopted in other iron- and steelmaking processes. Recognizing the close relationship between AI techniques and progress in iron- and steelmaking, Kawasaki Steel has established an AI information committee to evaluate AI technology and promote its adoption.

Until around 1980, iron- and steelmaking followed the classic model of a mass production process and was characterized by increasingly large equipment, higher production speeds, and process integration. Beginning in the latter half of the 1980s, however, all the major Japanese steelmakers put enormous effort into materializing flexible manufacturing systems (FMS) which would make it possible to produce a wide range of products in small lots using what were essentially a mass-production facilities.[1] The key word in this period was "chance-free," a term used to describe production processes in which scheduling, volume, and other constraints had been substantially eliminated.

AI is extremely useful in achieving the higher levels of process automation which are a requisite condition for EMS process technology. In the steel industry, "automation" means more than simple replacing men with machines; it also includes the systemization of information processing and judgment functions. In steel's new FMS era, an essential condition is the extension of the range of objects of automation to include not only the well-structured problems of the age of mass-production but also ill-structured problems. The development and introduction of AI technology is expected to play a key role in this regard. More specifically, the steel industry has entered a period in which the objects of automation include not only well-structured problems such as BOF blowing control and the control of sheet thickness and flatness, but also ill-structured problems such as the optimization of multiple processes and the control of blast furnace condition.

On the other hand, even in systems which have already been successfully automated as well-structured problems, new operating conditions, including the diversification of product types and need for better accuracy

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and chance-free operation, have created tasks which can best be managed by human intelligence and/or experience. The obsolescence of the previously developed systems of automation has thus also become a problem. AI technology also offers promise in this regard.

This report describes the current status and future outlook for AI efforts at Kawasaki Steel.

2 AI and Rationalization of Production Processes in Steel Industry

In recent years, innovation has been required in the steel industry from the following points of view:

(1) Development of new production processes per se
(2) Rationalization of material flow in total production process
(3) Improved yield, improved unit consumption performance
(4) Process automation, manpower savings
(5) Development of higher value-added products

Typical examples in each of these categories are: Changeover from slabbing to continuous casting, changeover from batch annealing to continuous annealing (1); integration of continuous casting and hot rolling into continuous process (2); development of precision rolling technology and models for hot finishing mill (3); trend toward no-man operation of reforming line (4); and diversification of surface treatments for cold rolled steel products (5).

Through rationalization efforts of this type, a manufacturing system for small-lot, multi-kind production has been materialized in the iron- and steelmaking process. For example, in the integration of continuous casting and hot rolling into a continuous process, it was necessary to overcome inherent differences in the characteristics of the continuous casting and rolling processes (e.g. differences in capacity and in the size of material units) in order to create a manufacturing technology capable of producing products with the required properties in spite of product-mix restrictions at the rolling stage. This was achieved through the development of heavy reduction rolling mills[2] and comprehensive software based on the new operation concept of FMS, which aimed at obtaining maximum performance from existing reheating furnaces and rolling mills.[3] Several batch-type processes have also been combined into a single continuous process, for example in the continuation of the cold tandem mill and pickling line. As with hot rolling, it was also necessary to develop systems and control techniques suitable for chance-free operation.

A first step in the creation of flexible manufacturing systems involving the integration and synchronization of individual processes is automation of the material flow by the thoroughgoing elimination of manned material handling by crane. The features of FMS in the subsequent stage of development are then:

(1) Operation based on control information obtained from sensors and process control models rather than conventional visual information
(2) Application of control algorithms in place of manual intervention by mill operators
(3) Use of high-density information covering a wider range of upstream and downstream processes
(4) Rational automation of operating sequence schedules, which had formerly been the responsibility of operators

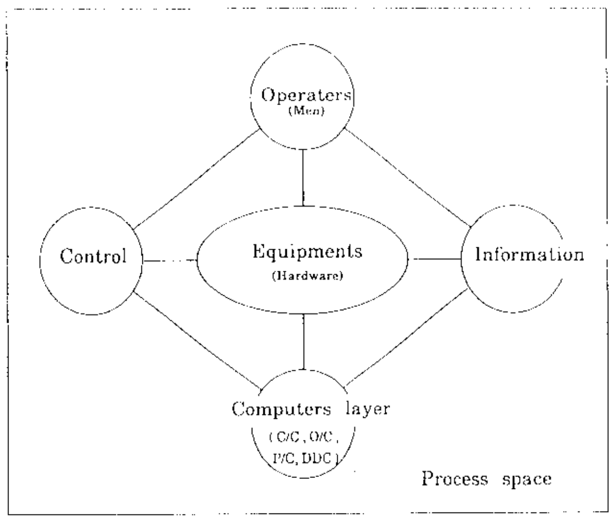

Fig. 1 Structure of iron and steel processing

FMS developed as a system supported by decision-making based on the knowledge of specialists, which is the basic definition of an expert system.[4] Kunieda is correct in pointing out that "expert systems did not come into existence because of AI technology,"[5] since quasi-expert systems had been realized at a relatively high level in iron- and steelmaking processes.[6] Even if these did not take the form of knowledge-based systems, it can be said that they are providing an adequate base for the introduction of AI technology.

The conceptual structure of the iron- and steelmaking process is shown in **Fig. 1**. With equipment as its central element, it is comprised of the human element (operators), information, control, and the various levels of computers. Although the human element has been virtually eliminated from some automated processes, it is not possible to do away completely with the man/information and man/equipment relationships, since the human presence is important in the monitoring of abnormal process conditions, intervention to correct such abnormalities, information processing and judgment in response to schedule changes, and other process control functions.

A precondition for the introduction of AI technology is quantification of process conditions and information, and the standardization of operating practices in terms of such information. In consideration of this, multifaceted computerization of all processes is necessary. By way

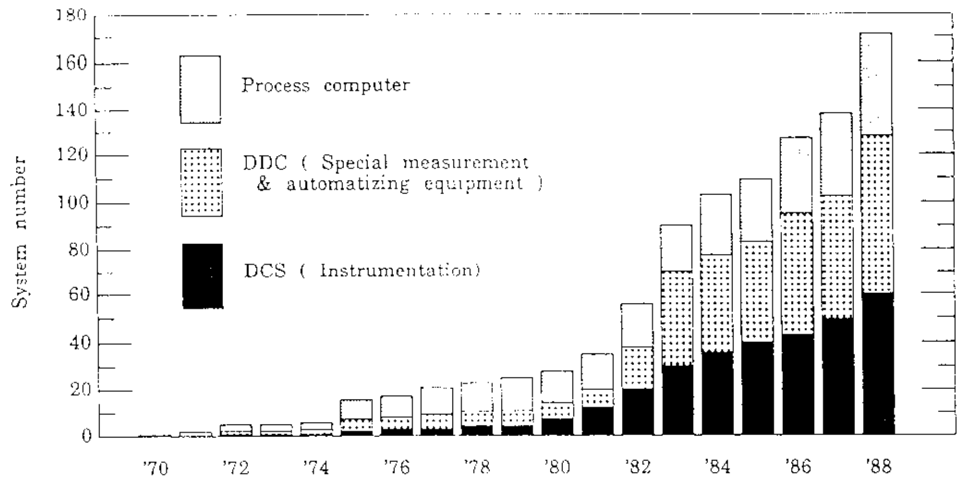

Fig. 2 Increase in the number of digital control systems and process computers (Mizushima Works)

of example, **Fig. 2** shows the trend in the number of process computers in use at Mizushima Works and should make it clear that active development of process computer systems since 1980 has, step by step, laid the groundwork for the introduction of AI.

Such efforts to introduce new equipment and provide a broader and more substantial range of control and information processing functions have resulted in an increasingly dense relationship between the human element and other three elements (control, information, and computers). Because of both process needs and the system environment, great hope is placed on AI technology for the realization of a higher level of performance in FMS processes. The reason for this expectation is that improved control accuracy (including control functions related to well-structured problems), better equipment reliability, and greater density and inclusiveness of information are required, and AI technology is expected to provide a methodology for the automation of the role played by the human element relative to each of these three elements. For example, local optimization control has been realized in some areas, but comprehensive process optimization requires automation of processes such as the blast furnace which depend on operator skill, automation of the equipment and process diagnosis functions, and automation of planning tasks where it is difficult to define clear and distinct evaluative coefficients or produce quantitative models.

3 Application to Iron and Steel Production Systems

Figure 3 is a conceptual diagram of functions in the iron- and steelmaking processes from the viewpoint of software rather than hardware. These functions are defined as follows:

(1) Planning

Manufacturing instructions are given to production lines by business computers (C/C or O/C). The content of such instructions includes not only pro-

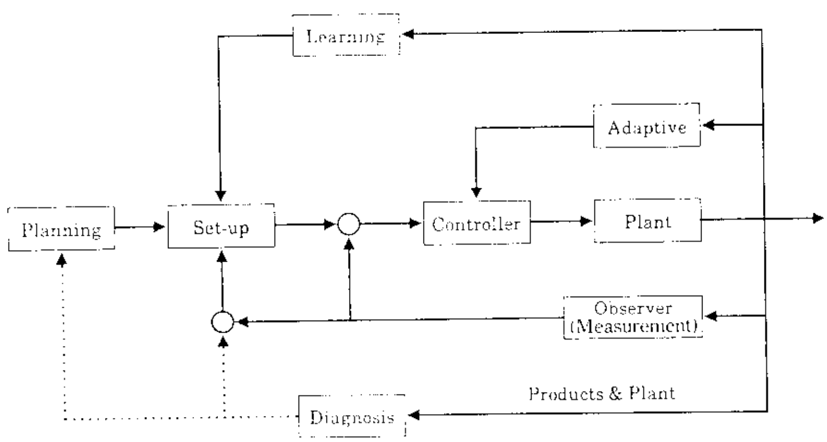

Fig. 3 AI functions structure of iron and steel processing

Table 1 Examples of AI applications

Problem types		Applications	Process: Raw materials	Process: Ironmaking, Energy	Process: Steelmaking, Cont. casting	Process: Rolling, Pickling, Cont. annealing	Process: Stainless steel, Surface finishing, Silicon steel	Process: Warehouse, Shipping yard	Process: Others
Analysis problem	Monitoring (interpretation)	Prediction of blast furnace temperature (NN)		○					
		Automatic recognition of marked letters on slabs (NN)			○				
		Classification of surface defects (NN)					○		
		Pattern recognition of microstructure photograph							○
	Diagnosis	Diagnosis of coilling machine				○			
		Diagnosis of hydraulic reduction system in cold tandem mill				○			
		Diagnosis of automatic gauge control system in cold tandem mill				○			
		Diagnosis of surface quality of hot rolling coil				○			
		Diagnosis of surface quality of coil as products				○			
		Diagnosis of silicon steel quality					○		
		Diagnosis of rotating machines							○
		Abnormarity diagnosis of software programs							○
		Abnormality diagnosis of computer terminals							○
	Control setup	Dynamic control of conveyors between ore preparetion plant and sinter plant	○						
		Sinter plant automatic control	○						
		Sinter process burning point control (FZ)	○						
		Ore sizing plant automatic control (FZ)	○						
		Coke oven combustion control (FZ)	○						
		Steam pressure control in steel works		○					
		Blast furnace operation control		○					
		Granulated slag bunker operation control		○					
		Burden distribution control in blast furnace		○					
		Hot stove conbustion control (FZ)		○					
		Flux and coolant charging control			○				
		Billet flow control in conditioning yard				○			
		Slab reheating furnace combustion control				○			
		Automatic control of entrance table of cooling bed in plate mill				○			
		Rolling speed control in tandem mill				○			
		Pacing control in slab reheating furnace in hot strip mill				○			
		Optimum speed control in continuous annealing process				○			
		Rolling control in dull surface strip				○			
		Strip temperature control in No.3 pickling line				○			
		Coil buggies optimum operation control in EGL yard					○		
		Coating control in continuous galvanizing process					○		
		Stainless steel coils automatic transportation control					○		
		Electro-magnetic coils automatic transportation control					○		
		EGL products quality control					○		
		Box furnace temperature control (FZ)					○		
		Stainless steel coil automatic transportation control						○	
Synthesis problem	Planning (including design)	Ore bunkers assignment plan	○						
		Raw material coal blending plan	○						
		Seamless pipe rolling schedule				○			
		Stainless steel materials ordering schedule				○			
		Slab charging schedule in batch furnace				○			
		Manufacturing schedule in pickling line				○			
		Rolling schedule in No.4 tamdem mill				○			
		Small size coils build-up schedule					○		
		Slitter assignment plan in silicon steel line					○		
		Automatic design of coil combination					○		
		Berth plan for plate shipment						○	
		Vehicle assignment for product shipment						○	
		Ship's stowage plan for steel products						○	
		Berth plan for product shipment in steel works						○	
		Berth plan for raw materials carrier						○	
		Consultation for use of MARC (structure analysis package)							○
		Support system of creep test							○
		Patent manuscript guidance system							○
		Repairing support guidance system for water pipe lines							○
Others	Learning	Automatic rule acquisition in cooling bed control system				○			

NN : Neural networks FZ : Fuzzy theory

duct specifications, but also planning of the sequence in which orders will be processed, scheduling, and the makeup of production lots from various customer orders.

(2) Setup
This system calculates initial values for line controllers based on manufacturing instructions and values measured at the site and/or predictive calculated values. Optimization calculations are made for the steelmaking converters and rolling mills based on quantitative models.

(3) Controller
This function is performed by DCS and PLC units. Generally, plant actuators (motors, valves, cylinders, etc.) are controlled on the basis of feedback values obtained at the plant by high-speed control sampling.

(4) Monitoring
The physical state of the plant and products is measured and predictions are made using models.

(5) Adaptive Function
Controller gain and parameters are modified dynamically on the basis of plant and product conditions so as to optimize the control loop.

(6) Learning
Parameters in the setup model prediction function are corrected using actual plant output values (output of monitoring function).

(7) Diagnosis
This is a comprehensive judgment function which uses equipment signals, operational signals, and measured values for products to determine respectively the soundness of hardware, operations, and product quality.

Material flow is among the most often discussed topics in connection with the development of FMS in the steel industry. In automated material flow processes, personal computers perform the administrative part of the planning function and the setup function. Product and transport vehicle position are tracked using signals of the observe function. Vehicle and product assignments are made and vehicle routes are determined so as to optimize the flow of material, which usually means ensuring the maximum use of the handling capacity of yards. It should be noted that the conceptual diagram in Fig. 3 can be used to describe this type of discrete-time system as well as continuous-time systems such as mill control.

Table 1 shows AI systems either already developed or now under development at Kawasaki Steel, categorized in terms of both process/products and the software functions listed above. The list includes examples of technology developed simultaneously at Chiba Works and Mizushima Works and of technology transferred between the two plants. For this reason, some systems such as blast furnace control are listed as one item, although developed and/or practiced at both locations.

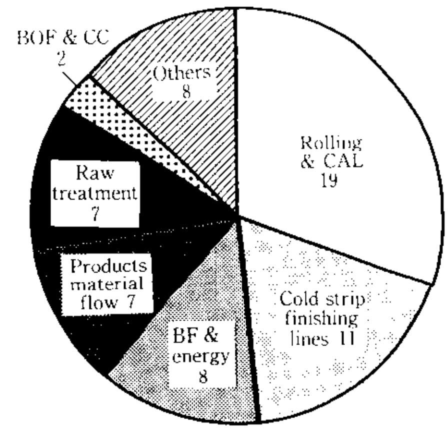

Fig. 4 Process classification of AI applications

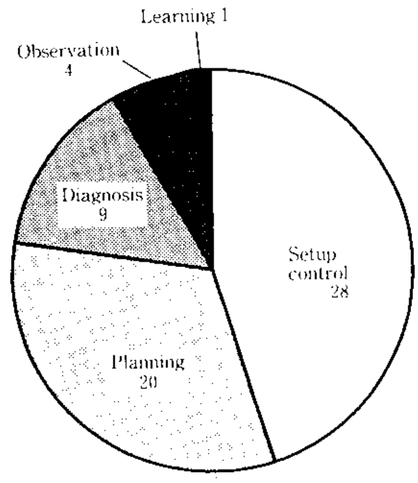

Fig. 5 Problem classification of AI applications

Figure 4 is a summary of the relative number of AI systems applied by production process; **Fig. 5** is a summary by AI function. Notable features of these systems are described below.

3.1 Measurement Problems (Interpretation of Data)

With the exception of batch-type processing problems in image processing tasks such as the extraction of data from photographs of metal microstructures, where a rule base is used, the principal AI method adopted in measurement problems is the neural network.

In a neural network, the weight of input variables of the nonlinear coefficient of each neuron is determined relative to a given teacher model by the back propagation method. Once the network structure has been decided, high-speed processing of categorical outputs to the teacher pattern is possible for a variety of input signals. The recognition of characters marked on slabs at the continuous caster[7] and prediction of trends in furnace heat at the blast furnace[8] are examples of application. It is also possible to classify defects on the surface of steel sheets by applying pattern processing to defect input signals obtained by laser or photoelement detectors. Moreover, it has been difficult with only conventional statistical data processing to perform feature extraction on some objects which require high-volume distributed signal processing or process analysis with large volumes of long-term data; the neural networks used in applications of the types mentioned above are an effective means of performing such tasks and thus represent a method with considerable promise for expanded application.

3.2 Application to Diagnosis Problems

Diagnosis problems can be divided into three main categories: equipment diagnosis, operational diagnosis, and product quality diagnosis. A precondition for each type is a completed system for measuring and collecting process signals. However, the solution to such problems depends on the depth of knowledge possessed by equipment maintenance crews, operators, and quality control people more than on any other factor. Plant hardware has of course long included systems which notify the operator when measured signals reach upper or lower limits, but equipment diagnosis systems incorporating AI technology are now being applied with the following aims:

(1) Common use of expert knowledge
(2) Standardization of judgment criteria where individual differences exist
(3) Elimination of need for special skills in use of high-level systems

High-level diagnosis know-how is the product of trial-and-error methods and the accumulation of a great deal of experience, and is promising as an area application for AI technology. However, there are cases in which carefully developed equipment diagnosis systems have been rendered superfluous by improved maintenance capabilities, which made breakdowns a rare occurrence (e.g. No. 2 tandem oil-hydraulic screwdown equipment diagnosis[9]).

The history of Kawasaki Steel's advanced go-stop system illustrates how AI-type diagnosis systems are developed. The original go-stop system[6] provided operational guidance on the basis of blast furnace condition diagnosis, and was a type of operational diagnosis system. The deep knowledge of blast furnace operation cultivated in the development and use of this system became the base for a new expert system for blast furnace control (the advanced go-stop), which suggests the importance of measuring and collecting data as the basis for AI technology. In fact, the quantification of phenomena is basic to all types of diagnosis. As an example of product quality diagnosis, this special issue (Japanese version) include a report on an expert system developed for the cold tandem mill.[10]

3.3 Application to Setup Control Problems

Setup control problems have become a central task for AI technology. The object areas can be classified as follows:

(1) Processes such the blast furnace and sintering, which are characterized by a complex interrelationship between reactions and combustion and are difficult to reduce to numerically expressed model.
(2) Tasks such as control of sinter burn-through, hot stove combustion, and box furnace temperature, in which it is difficult to control the material being heated (or the completion of sintering) by simple PID control.
(3) Tasks such as control of the reheating furnace computer and cold dull rolling which have been treated as well-structured problems with good success, but to which AI technology can be applied effectively to realize higher levels of automation.
(4) Tasks such control of the finishing line material flow and coil transportation in the yards which do not necessarily require deep knowledge, but where AI supports better efficiency in program development and improved maintainability.

The relationship between control methodologies and the level of automation in the steel industry is shown in **Fig. 6**. The purposes of automation in steel processes include improvement in product quality and yield, operational stability, and manpower reductions. If automation is considered from the viewpoint of manning reductions, the operational configuration evolves through the following steps with the "manless workplace" as its ultimate form:

Total automation of operation → Unification of operation rooms → One pulpit → No-man operation

To obtain a unified view of the current operational configuration at Mizushima Works, the degree of no-man operation was defined as the unification ratio α. The number of items of equipment for which a single operator is responsible was then counted, and no-man operation was evaluated, as shown in **Fig. 7**.

$$\text{Unification ratio } (\alpha) = \left(1 - \frac{\text{No. of control desks} \times \text{No. of pulpits}}{\text{No. of items of functional equipment}}\right) \times 100$$

Low values of α indicate that little progress has been made in unification, while the value of α approximates 100 in the no-man factory. As may be expected, the operations with the lowest ratings were the finishing line and yards; rolling processes held the intermediate positions, and the greatest degree of unification was found at the process lines. An evaluation of the level of process automation clarifies the processes and problem areas to which AI technology can profitably be applied.

Although automation does not progress by the appli-

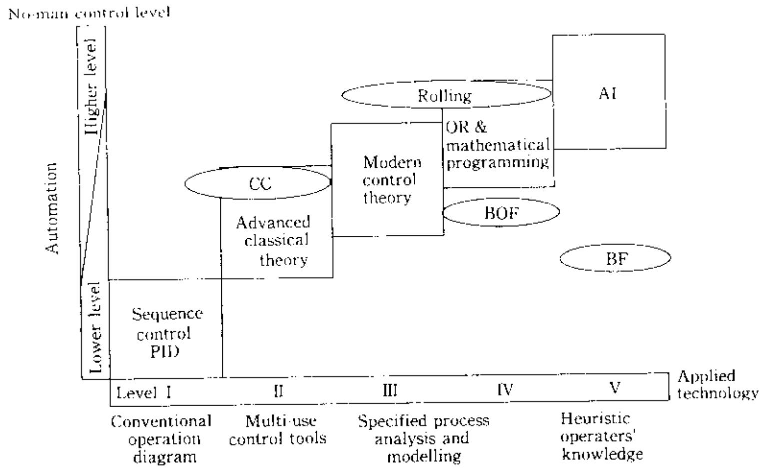

Fig. 6 Control methods and automation level

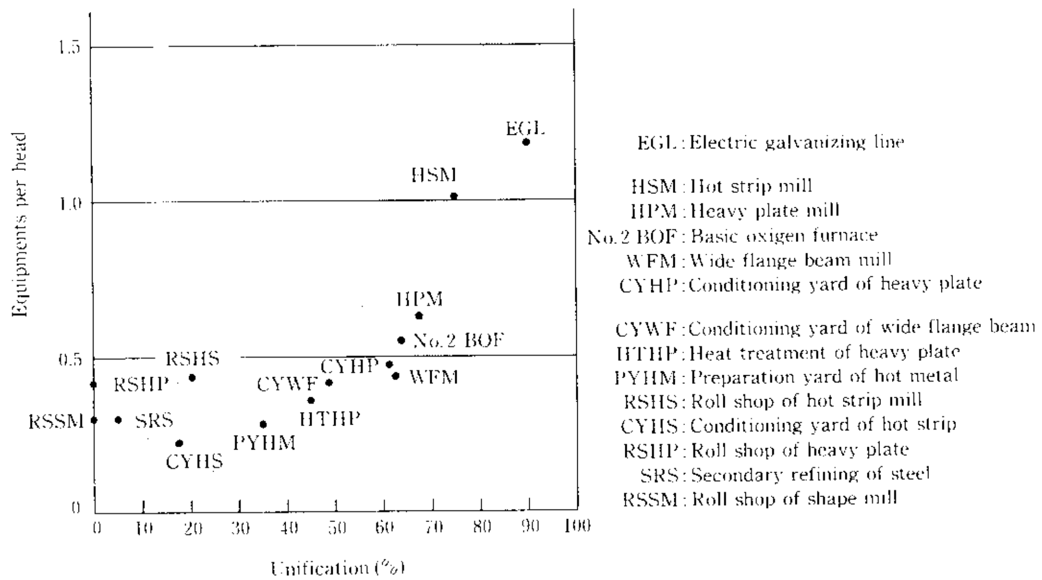

Fig. 7 Equipments per head and unification

$$\text{Unification} = \left(1 - \frac{\text{Cont. Desks} \times \text{Pulpits}}{\text{Num. of equipments}}\right) \times 100$$

cation of AI technology alone, as a greater degree of automation is achieved, the human/process interface becomes increasingly knowledge- and information-intensive. From this viewpoint, AI is an important support technology for operators. As an example of the use of AI technology in this supporting role, this special issue describes the previously mentioned AI system developed for blast furnace operation.[11]

3.4 Application to Planning Problems

Planning applications of AI technology can be divided into the drafting of basic plans (e.g. making up seamless pipe rolling schedules) and the revision of the basic plan for implementation when instructions for execution are given to the production line (e.g. berth plan for plate shipments, railway track scheduling for products sold to off-site users). The aim in the first case is improved solutions where contractual requirements are complicated or evaluative indices depend on surrounding conditions. This application takes advantage of the flexibility of AI technology in defining problems and providing the means of solving them. The aim in the latter case (revision prior to plan implementation) is to systematize the experience of skilled workers, which is generally difficult to reduce to basic standards and specifications, and thus preserve this body of knowledge for ongoing use. As a phase in system development, the latter process tends to come first, with planning as such assuming greater importance over time. This is because there is a pressing need for full- or at least semi-automation of the intermediary function between planning and actual operation—which currently depends heavily on experienced specialists—in the organization of the type of plan-directed production represented by the total production control system of the steelworks.

On the other hand, from the viewpoint of areas of application, material flow and shipping operations frequently take priority, with application to production control coming later. One reason for this is the great proportion of total steelworks labor which is devoted to what is broadly called "transport work," which includes activities ranging from raw materials receiving and handling to final product shipment. Material flow management is affected by operating conditions at each of the production lines and must perform a "buffering" or "cushioning" function by absorbing disturbing factors (unscheduled shutdowns, production bottlenecks, etc.), and is thus an ill-structured, difficult-to-systematize problem. It can also be said that this field has been given priority as an AI application because it is one main area in which systematization has lagged. Examples presented in this special issue are expert systems for preparing raw material coal blending plans[12] and seamless pipe rolling schedules[13] (the latter is only in the issue of Japanese version).

3.5 Application to Automatic Rule Learning

The learning functions incorporated in neural networks can be categorized as either automatic rule acquisition or automatic rule learning. This special issue (Japanese version) presents a system developed for the plate cleaning bed[14] by way of example. In developing the berth plan for plate shipment, plot-type development and the actual system itself required virtually the same amount of time, suggesting that research on the logic of the rule learning function and practical evaluation will be important tasks for the broader application of AI technology in the future.

4 Future Tasks

The application of knowledge engineering to actual processes has now made the transition from a temporary period of overheated enthusiasm to a stage of realistic activity. During the initial period of practical implementation, however, many problems related to AI concepts became apparent.[15,16] Kawasaki Steel's experience is summarized below.

(1) Although we may speak of "rule transparency," the "rule acquisition bottleneck" places limits on AI technology. The effectiveness of AI is limited by the amount of effective knowledge included in the rule base. At present, AI system design people (KE: knowledge engineers) use individual methods to extract knowledge from experts, but the relative merits and speed of this process are determining factors in both system performance and development time. The development of tools or some type of methodology for the knowledge acquisition process is needed.
(2) When rule acquisition is applied to systems for which operational procedures and technical standards are entirely lacking, the advantages of AI are not apparent at the system design stage. For example, when the berth plan for plate shipment was developed, the actual system required twice the manpower of plot type work.
(3) The software interface between AI and the conventional procedure program (incorporation of AI tools in host system) is cumbersome.
(4) A problem of excessive consumption of computer resources (memory, calculation time) frequently arises and is difficult to solve at the practical system level.
(5) AI system development is generally a cooperative effort by experts and KE people who are former systems engineers, but there is still a manpower shortage among knowledge engineers. So as not miss opportunities to apply AI in key operations, it is essential to develop KE people who are both well versed in conventional systems technology and in AI technology, and to provide tools which can be used by end-users.

In spite of these limitations, the benefits of the application of AI technology to iron- and steelmaking processes include the following three points:

(1) Expansion of range of problem-solving (e.g. blast furnace, material flow control)
(2) Improved efficiency in development of knowledge base programming software
(3) Quantification of latent knowledge

It is believed that the development of AI logic and computer technology will provide solutions to the problems mentioned above, making it possible to apply AI technology to iron- and steelmaking processes with even greater effect. On the other hand, Mizoguchi predicts growth in design and planning systems in the market for AI (**Fig. 8**). At Kawasaki Steel, these areas now account for close to 70% of AI systems if monitoring

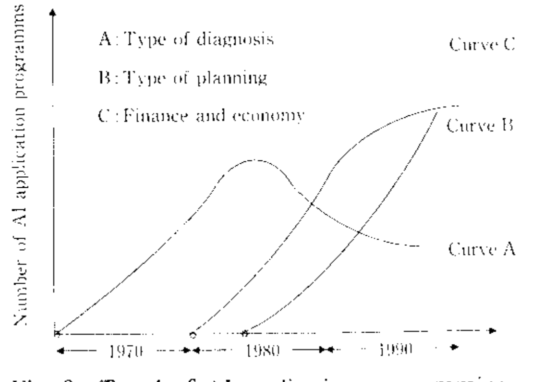

Fig. 8 Trend of AI application programming

and control are included, indicating that the company is already following the trend indicating Mizoguchi's B curve.[17] Examples in these areas are on the increase, for reasons which may be summarized as follows:

(1) As mentioned in Sec. 2, AI ranks as an effective means of achieving a higher level of intelligence in iron- and steelmaking processes.
(2) Because the number of experts with deep knowledge is gradually decreasing as the group ages and retires, the transmission of technology and skills is becoming a critical problem. Moreover, there is an increasing realization that fundamental knowledge in regard to operations is a company's greatest asset.
(3) The number of persons involved in AI research is increasing, and projects such as the "fifth generation computer"[18] and "steel plant FMS," which highlight the crisis in software, have in recent years been pursued by the government and business as joint industry/academic research tasks.
(4) The functional level of AI development tools has improved with progress in electronics.

The methodology of AI techniques has expanded from simple knowledge processing to include learning systems, neural networks, and human interface, resulting in a broader range of problem-solving applications.

5 Conclusions

With progress in the application of AI, this technology has established itself as an important system development technique. At the same time, workers in this field, while recognizing the current limitations of AI technology, also realize that greater practical return on AI projects is now expected by user firms. Development must proceed in consideration of the balance of effects which can be obtained by problem-solving in tasks which can best be solved by improving the accuracy of conventional models and control algorithms, and those in which AI methods are more appropriate. As a means of raising the intelligence level in production processes, the impact which AI has had on the steel industry includes its clearly demonstrated effectiveness as a methodology for problem-solving in large scale processes such as the blast furnace and in material flow, both of which have to date been difficult to manage using procedure-type software. In addition, technical tasks where conventional systemization was difficult have been thematized from the viewpoint of technology transmission, and development is proceeding accordingly. From this perspective, Kawasaki Steel is promoting the application of AI technology on the basis of a company-wide organizational structure.

In closing, a comparison may be made between the current stage of AI and the early application of the process computer. When the PC was first introduced, many wondered what practical application it could have, but control of today's iron- and steelmaking process would be impossible without it. Likewise, AI hardware and software is becoming an essential part of the iron- and steelmaking process, and the authors therefore look forward to the dawn of an era of more sophisticated FMS systems in the steel industry.

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