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THE ROLE OF DECISION SUPPORT SYSTEMS IN STEEL INDUSTRY

Mümtaz KARATAŞ*, Hakan GEÇİLİ*
*Kocaeli Üniversitesi, Kocaeli, Turkey

Abstract

A decision support system (DSS) is defined as a computer based information system that supports business or organizational decision making activities. DSSs are mainly used for serving the management, operations, and planning levels of an organization and they help decision makers in rapidly changing environments which are not easily specified in advance. Steel is one of the basic building blocks of the modern world such that automobiles, appliances, bridges, buildings, etc. all are made with steel. While steel manufacturing has existed for centuries, the ironmaking and steelmaking process continues to evolve and the complexity in those process increases. Trying to survive in an intensely competitive industry, the steel production companies try to improve their manufacturing processes and consolidating businesses continually to remain competitive in the global market for steel. For that reason today in steel industry the need for decision making speed has increased as well as the overload of the information. Currently there are a number of computer based DSSs used in various phases of steel production process and in this paper our purpose is to research the need for computer based decision making in steel industry and make a comprehensive review of decision support systems used in the industry.

Keywords: Decision Support Systems, Computer Based Decision

1. Introduction

Steel industry is an essential and considerable sector for modern industrialized economies. Since it is capital and energy extensive, companies have been putting emphasis on technology advances in the production process to increase productivity and to save energy [1]. Modern iron and steel corporations are moving towards continuous, high-speed and automated production process with large devices. The focus is placed on high quality, low cost, just-in-time (JIT) delivery and small lot with different varieties [2]. Another aspect of ironmaking and steelmaking processes is the high energy requirement issue. Energy represents more than 20% of the total cost of producing steel and is still rising [3]. The increasing cost of energy and even its current and future availability have led to the need to refocus attention on energy intensity in steel production. Under such constraints, trying to survive in an intensely competitive industry, steel production companies look for methods to improve their manufacturing and scheduling processes and consolidating businesses continually to remain competitive in the global market for steel. Using high-end decision support systems (DSS) at various phases of steel manufacturing and switching human judgment with computer based systems is an amendment in the industry and this method is adopted by several organizations.

In the literature, the number and content of academic studies and scientific papers related with the decision support systems and intelligent expert systems used in the steel and iron industry is very limited. In [4] a fuzzy multi agent system for ironmaking and steelmaking process is presented. In the study each process of ironmaking and steelmaking is regarded as an independent agent and each agent is in contact and cooperation with other agents in the system. The method used to generate the knowledge basis of agents is adaptive neuro fuzzy inference system. In [5] is presented a decision support system that is created for identifying a steel or cast iron from a microphotograph. However, the crucial intend of the procedure applied is to assist metallography student who are learning the concepts related to identifying and classifying steels and cast irons. In [6], applications of neural networks to the administrative control of a reheating furnace in the steel

Corresponded Author; mumtaz.karatas1@kocaeli.edu.tr

and iron industry are presented. Also there are some other scientific papers and technical reports about the problem of scheduling of various steel making processes such as rolling, casting, scrap charge by using methods like fuzzy multi agent systems [7-10].

In the following sections, we first briefly review the ironmaking and steelmaking process and the steel life cycle in Section 2. Then in Section 3 we give information about the DSSs and in Section 4 we summarize the DSSs used in the steel production industry. Finally we give a brief summary in Section 5.

2. Manufacturing Processes and Life Cycle

2.1 Ironmaking and Steelmaking Process

To understand the complexity and the necessity of using computer based decision tools at different stages of the ironmaking and steelmaking process it is important to understand the complexity of production process and the technology used in modern steel production companies. The production of steel at an integrated iron and steel plant is accomplished using numerous interrelated processes. The main processes executed are coke production, sinter production, iron production, iron preparation, steel production, semi-finished product preparation, finished product preparation, heat and electricity supply, and handling and transportation of raw materials as well as intermediate and waste materials. The complex interrelation of all these operations is demonstrated in a flow diagram of the iron and steel industry in Figure-1 [11].

Examining the interrelation of all operations, it is unavoidable to face a variety of resource planning, optimization, scheduling, etc. problems in ironmaking and steelmaking process. For instance, production scheduling problems are to determine in what sequence, on which equipment and at what time molten steel should be arranged at various production phases from steelmaking to continuous casting. Unlike general production scheduling in machinery industry, scheduling problems faced in steel production have to meet special requirements of steel production process. In this process, the products being processed are handled at high temperature and transformed from molten steel (liquid form) into drawn billets (solid form). There are extremely strict requirements on material continuity and low time (including processing time on various equipments and transportation and waiting time between operations) [12]. Therefore to compete in the competitive industry companies prefer using automated systems and computer based decision tools or expert systems to optimize the processes, resources and increase efficiency by reducing risks associated with human factors.

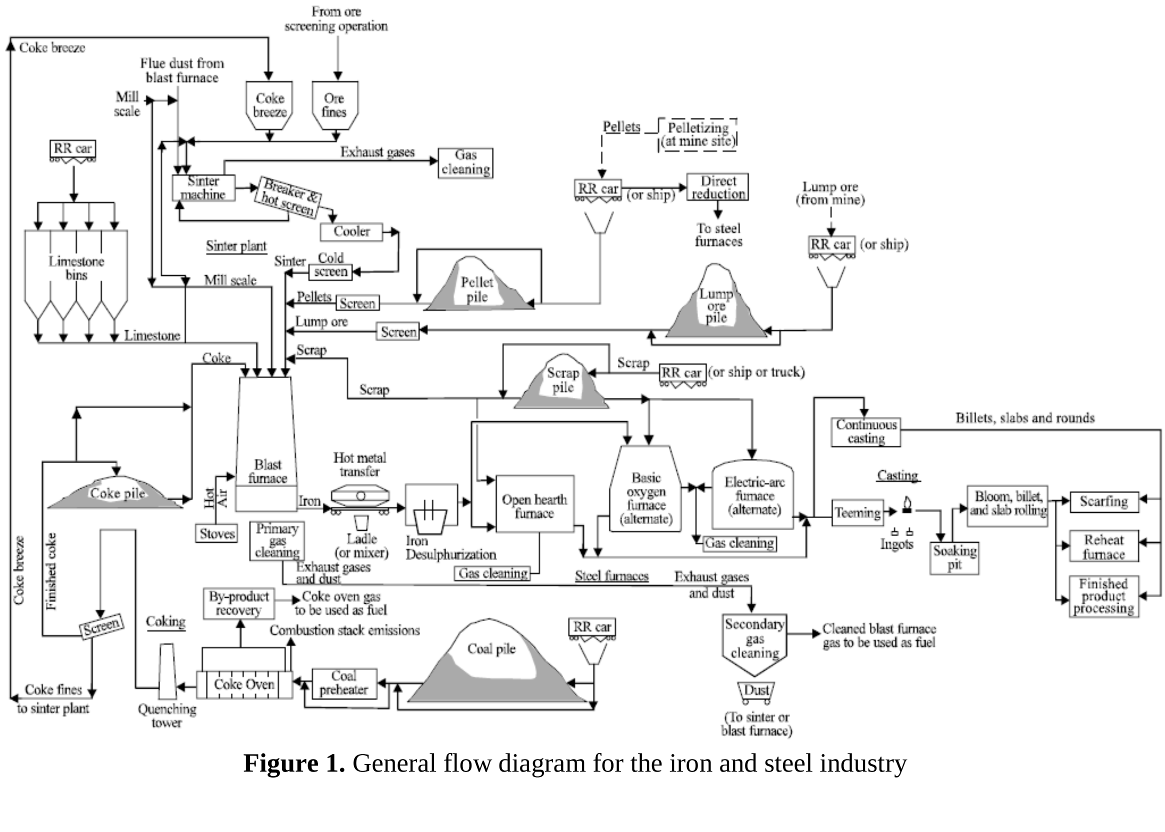

Figure 1. General flow diagram for the iron and steel industry

2.2 Life Cycle of Steel

The life cycle of steel is illustrated in Figure-2. Steel can contribute to the environment from the stand points of steel manufacture and products in the following four main phases [13]:

- Steel manufacture from raw materials to finished steel products.
- Fabrication and assembly of final products using steel.
- Use of final products.
- Scrapping or recycling for reuse.

In the first phase the main concern is the steel manufacturing process itself. It is crucial to manage the steel production processes with economical use of energy and efficient methods that alleviate the load to the environment. The manufactured steel is used to contribute to the needs of the customers in phase two. In depends on the type of steel used to control the environmental load. In the third phase the actual final products are used by the customers in accordance with their needs. For instance, high-quality steel products are used in developing economical and low fuel consumption type of automobiles and the efficiency improvement of motors. In the fourth phase, the products that are used by the customers are scrapped and recycled. In this phase, under normal conditions the steel scraps are returned to the steel industry.

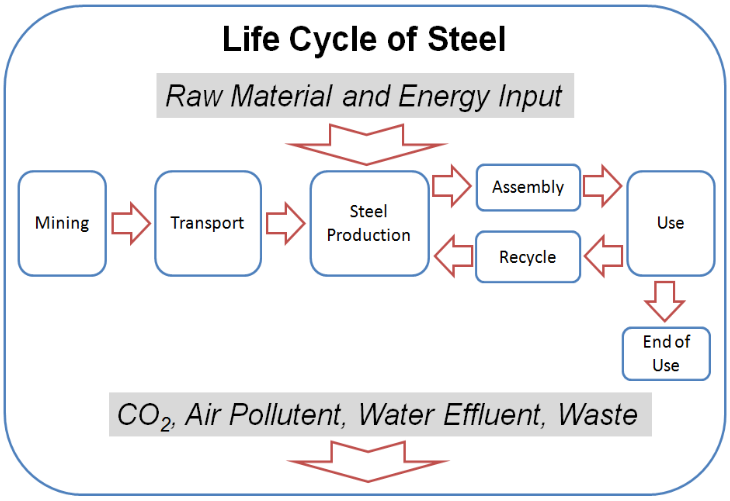

Figure 2. Life cycle of steel

3. Decision Support Systems (DSSs)

There is a considerable amount of empirical evidence that human intuitive judgment and decision making can be far from optimal, and it worsens even further with complexity and stress. In many situations the quality of decision is very important. Because of this assisting the insufficiencies of human judgment and decision making has been a main focus of science throughout history. To enable making rational choices disciplines like economics, operations research and statistics developed many methods. Nowadays, these methods, often improved by many techniques deriving from artificial intelligence, information science and cognitive psychology, have been used in computer programs, either as stand-alone tools or as integrated computing environments for complex decision making. Such environments are generally given the name of decision support systems (DSSs).

DSS is also known as knowledge-based systems, because they attempt to formalize domain knowledge so that it is amenable to mechanized reasoning.

DSS can assist human cognitive insufficiencies by combining different sources of information, providing intelligent access to relevant knowledge, and assisting the process of structuring decisions. DSS can also support choosing between well-defined alternatives and build on formal approaches, like the methods of operations research, engineering economics, statistics, and decision theory.

DSS can also use artificial intelligence techniques to address heuristically problems which don't give solutions by the use of formal methods. Good use of decision-making methods increases efficiency, productivity and effectiveness and gives a comparative advantage over their opponents, allowing them to make optimal choices for technological processes and their parameters, planning business operations, logistics, or investments. [14]

There is much anecdotal and some empirical evidence that structuring decision problems and identifying creative decision alternatives determine the ultimate quality of decisions. DSSs mainly aim at this broadest type of decision making, and in addition to supporting choices, they aid in modeling and analyzing systems (such as complex organizations), identifying decision opportunities, and structuring decision problems [14]. Having all these enhanced features and aspects, the demand for DSSs in various industries increase day by day.

The spectrum of applications of DSSs technology to industrial and commercial problems is so wide as to defy easy characterization. The applications find their way into most areas of knowledge work. They are as varied as helping customer service desks to find solutions to the problems they face to military decision aid tools that support the commanders decision in combat. The DSS applications tend to cluster into seven major groups.

a. Diagnosis and Troubleshooting of Devices and Systems of All Kinds: This class comprises systems that deduce faults and suggest corrective actions for a malfunctioning device or process. Medical diagnosis was one of the first knowledge areas to which DSS technology was applied The diagnostic problem can be stated in the abstract as: given the evidence presenting itself, what is the underlying problem/reason/cause?

b. Planning and Scheduling: Systems that fall into this class analyze a set of one or more potentially complex and interacting goals in order to determine a set of actions to achieve those goals, and/or provide a detailed temporal ordering of those actions, taking into account personnel, materiel, and other constraints. This class has great commercial potential, which has been recognized. Examples involve airline scheduling of flights, personnel, and gates; manufacturing job-shop scheduling; and manufacturing process planning.

c. Configuration of Manufactured Objects from Subassemblies: Configuration, whereby a solution to a problem is synthesized from a given set of elements related by a set of constraints, is historically one of the most important of expert system applications. The technique has found its way into use in many different industries, for example, modular home building, manufacturing, and other problems involving complex engineering design and manufacturing.

d. Financial Decision Making: The financial services industry has been a vigorous user of expert system techniques. Advisory programs have been created to assist bankers in determining whether to make loans to businesses and individuals. Insurance companies have used expert systems to assess the risk presented by the customer and to determine a price for the insurance. A typical application in the financial markets is in foreign exchange trading.

e. Knowledge Publishing: This is a relatively new, but also potentially explosive area. The primary function of the expert system is to deliver knowledge that is relevant to the user's problem, in the context of the user's problem. The two most widely distributed expert systems in the world are in this category. The first is an advisor which counsels a user on appropriate grammatical usage in a text. The second is a tax advisor that accompanies a tax preparation program and advises the user on tax strategy, tactics, and individual tax policy.

f. Process Monitoring and Control: Systems falling in this class analyze real-time data from physical devices with the goal of noticing anomalies, predicting trends, and controlling for both optimality and failure correction. Examples of real-time systems that actively monitor processes can be found in the ironmaking and steelmaking and oil refining industries.
Design and Manufacturing

These systems assist in the design of physical devices and processes, ranging from high-level conceptual design of abstract entities all the way to factory floor configuration of manufacturing processes.

One might expect that experts in a domain will not be subject to judgmental biases and will be optimal in decision making. While empirical facts show that professionals in fact are more accurate than apprentices in the field of expertise, it also shows that professionals also are liable to the same judgmental biases as apprentices and show obvious errors and inconsistencies in their decisions.

To make better decisions, decomposing a decision problem into simpler parts which are well defined and well understood is good way which many of even easy linear models over human intuitive judgment suggests. Studying a complicated system built out of such parts can be consequently assisted by a formal, theoretically sound technique. Decomposing and formalizing process of a problem is often called modeling.

4. Using Decision Support Systems in Steel Industry

There is a variety of decision support systems used in the steel production industry to support decision makers at different phases of the production. In this section we summarize some of these softwares, systems and give brief information about the methodologies and techniques used in these systems. Looking at the procedures conducted in the ironmaking and steelmaking industry, it is common to see that one or more tasks carry stochastic properties in terms of time required to operate, start/end time, material percentages, environmental conditions, etc. From this stand point fuzziness is a feature that must be taken into consideration in these processes. In [15] presented a new multi-agent DSS based on adaptive neuro-fuzzy inference system to help an operator to determine the amount of additive materials in steel-making process. Since the percentage of elements in steel-making usually has a fuzzy nature, the fuzzy rule sets defined by the designer and adaptive neuro-fuzzy systems are more precise and robust to model this complex decision problem.

Looking at [16], the DSS KOSIMEUS incorporates with a popular fuzzy systems methodology, the fuzzy PROMETHEE. This new DSS is a combination of process models simulated with flow-sheeting program and a multi-criteria DSS and it basically evaluates techniques which take into account ecological and so-called techno-economic criteria that describe the operational and other fixed costs depending on the technical performance. The method enables the user to get an insight into the preference structure of the decision maker and it also enables the user to concentrate his/her attention on critical issues related with the steel production phases.

Sequencing and scheduling is another important and common form of decision making that plays a crucial role in manufacturing and service industries [17]. Scheduling can be defined as the process of deciding how to commit resources between a variety of possible tasks [18]. If there are several resources are considered in a system then the problem of finding a feasible or optimal allocation of all operations to resources under some constraints may arise. The REPLAN system is a computer based decision support software that supports humans in generating schedules for high grade steel making in Böhler in Kapfenberg, Austria. The problem with the four production lines the company has is the variety of metallurgical grades used in the process and the diversity of chemical, spatial and temporal constraints. The main goal of the DSS is to generate sub optimal or local optimal schedules [19, 20].

SCHEPLAN is another scheduling expert system kernel used in the steel industry. It is the earliest available expert system developed for scheduling purposes and it was developed by IBM Tokyo for NKK Corporation [21]. The main purpose of the system was to shorten the average length of queues piling up before the casting units. The approach used in designing a schedule that satisfies the constraints (i.e. continuous use of machines, resting time requirement for machines, preemption issue) is not to obtain an optimal solution. Defining an evaluation function which leads to an optimum solution results in a very long processing time for the DSS, so it is preferred to obtain a sub-optimal or a feasible solution in an efficient way and in a reasonable time. The method used in the system is to follow a cooperative schedule method which efficiently generates a candidate schedule by a sub-scheduling and merging method. Within the help of the program, the time spent for scheduling was shortened from three hours to thirty minutes and the average waiting time in the queue became %50 shorter than before [21].

The purpose of a blast furnace is to chemically reduce and physically convert iron oxides into liquid iron called "hot metal". The raw materials require 6 to 8 hours to descend to the bottom of the furnace where they become the final product of liquid slag and liquid iron. The purpose of nearly all managers of blast furnaces is to achieve a standardization of control on a high quality production. Since the data available is ambiguous in most situations, it is hard to find or generate an uncomplicated control algorithm for the system. Several companies use now expert systems or DSSs for the supervision and control of blast furnaces. The benefit of an expert system is the possibility to build a model of the physical and chemical process in the furnace with symbolic values. Rules allow the specification of definite standards, when and how an operator should react.

An example of the companies that use a DSS for optimizing the blast furnaces is the Nippon Steel company which uses the ALIS DSS system for several blast furnaces which is explained in detail in studies [22] and [23]. Comparing the human performance with the ALIS system performance, the results show us that expert system performs almost 25% better than the humans in processes and humans decide better in 7% of the times. The system is continually developed and updated to support the decision processes in a more efficient way.

Another DSS developed for supporting blast furnaces is for the plant of NKK [24]. The computer based DSS works in cooperation and directly linked with the blast furnace system. To generate feasible and efficient solutions in a reasonable time the sensor data is preprocessed and only symbolic and trend data are delivered to the DSS. The number of decision rules defined and introduced to the DSS is reduced by using certainty factors and three dimensional membership functions.

Another aspect of the DSSs and expert systems used in the industry of ironmaking and steelmaking are that they are mostly one-user front end computerized systems committed to only one function to specialize in that area. Having that property, just as combining agent based systems to a centralized referee or decision system, it is very easy to integrate the DSSs with the existing organization. By that method, it is easy to couple several systems with a process computer or with a production scheduling system. However, if a stronger pairing is realized, DSSs or expert systems can be more beneficial to the decision user. It is demonstrated by means of experiences in the steelworks at Linz [25] and the four DSSs are explained below. A superior feature of the last four DSSs explained below is that those DSSs are not coupled but they produce and share knowledge that is used by others. The potential process routings generated by the third expert system (Computer Aided Quality Control (CAQC)) are stored together with the CAQC prescriptions in a data base and the second expert system has access to this data base. However, it cannot use the knowledge to decide whether exceptions to this process routings can be made to react on disturbances in the production process. The first DSS delivers lists of heats to the second DSS and the amount of available hot iron or breakdowns of machine information are not considered in this process. A kind of negotiation between both expert systems seems to be a promising approach to minimize the stored slabs and to be flexible on irregularities in the production process. If it would get data and information from the other DSSs which describe the complexity to manufacture certain grades of steel, the classification system described in the second section would be the most effective one among others. Since the characteristics will change over time due to aspects like the steel market, new production technologies, and new products, it is preferable to get the knowledge from these systems that have the relevant competence [25].

A DSS was set up to produce casting schedules for the rolling mill in a steel plant. The steel plant receives the order lists and the expert system applies information concerning feasible rolling sequences in the mill and abstract information regarding the ironmaking and steelmaking capability of the plant and its purpose is to minimize inventories between both plants [26].

In order to support the dispatchers in fine planning phase of a scheduling, an expert system was developed in the industry of ironmaking and steelmaking. The intention is reactive scheduling such as the reaction needed when breakdown of machines occur [27].

In order to realize the desired steel quality, a Computer Aided Quality Control (CAQC) system produces dependent on customer orders and steel grades prescriptions. These are not complete in aspects like process routings and settings of process factors for heats in the plant. To have guidelines and systematic procedures to help the decision maker and generate some feasible solutions, an expert system is developed and used in the industry [28].

To analyze the blast furnace an expert system was developed with the characteristics as described previously. It works interactively and does not control the furnace directly [28].

In [25] is described a task-oriented design for a scheduling applications in scheduling of production processes of a ironmaking and steelmaking plant. In this application each scheduling problem faced in the manufacturing process is considered separately and the solution is based on the orientation of the task such as minimization of the total wait time, average wait time, maximum wait time, or minimizing the difference among wait times of various jobs.

5. Summary

Our main motivation in this study is the objective to compile the DSSs that are used in the steel industry and to give a brief overview of the systems and methods used to optimize or solve the problems faced in the steel production processes. Having a very limited number of academic studies and scientific papers in the literature, we first give an overview to the ironmaking and steelmaking process and the life cycle. Since for a general approach of improving the automation, methods for coping with complexity and uncertainty are necessary, DSSs, by definition, can aid human cognitive deficiencies by integrating various sources of information intelligently. After giving information about DSSs, we summarize the DSSs used in the industry. Some of the methods used in these softwares are neuro-fuzzy inference system, PROMETHEE methodology, schedule generators, models of physical and chemical processes, task-oriented designs, fuzzy multi agent systems, neural networks, etc. The data we have for some of the DSSs show that they increase the efficiency in the processes when compared with the systems having merely human decision makers. However companies should not forget that they are responsible for the maintenance of these softwares and systems and they must give enough importance to the maintenance, updating and upgrading of such systems to be able to compete in the industry. It is possible that in the future, DSSs used in the steel production industry will heavily rely on a complex and well-designed network of DSSs. Also the future requirements for the DSSs both in steel and ironmaking industry will include more complex and dependent relationships among all production phases. Similar to creating agent-based systems, numerous small DSSs competing in a narrow domain will unite and form one big complicated but efficient DSS. The main challenge would be the communication and information sharing among the sub-DSSs.

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