Light Metals 2011 *Edited by: Stephen J. Lindsay*
TMS (The Minerals, Metals & Materials Society), 2011

Light Metals 2011

ALUMINUM REDUCTION TECHNOLOGY

Poster Session

SESSION CHAIR
Abdulla Habib
Aluminum Bahrain- Alba
Manama, Bahrain

Light Metals 2011 *Edited by: Stephen J. Lindsay*
TMS (The Minerals, Metals & Materials Society), 2011

HUMAN FACTORS IN OPERATIONAL AND CONTROL DECISION MAKING IN ALUMINIUM SMELTERS

Yashuang Gao[1,2], Mark P. Taylor[2], John J.J. Chen[1], Michael J. Hautus[3]
[1] Chemical & Materials Engineering
[2] Light Metals Research Centre
[3] Department of Psychology
The University of Auckland, Private Bag 92019, Auckland 1142, New Zealand

Keywords: Human factors, decision making, aluminium smelting, process control

Abstract

The aluminium smelting process involves highly complex mechanisms and has rich information but low observability. To operate such a process at maximum current and energy efficiency while striving for continual improvement requires a set of scientific and systematic approaches to problem solving and decision making along with constant human intervention and interaction based on informed and considered judgment. Understanding the influence of human factors on the process is important to the improvement of the performance of the operational staff and enhancement of positive impact while minimising negative effects on the process. This paper explains some aspects of the human factors and decision making involved in the smelting reduction operations and control process, which includes sensing and monitoring signals, identifying abnormalities and implementing appropriate responses to not only correct the immediate causes of the identified problems but also to reduce the variation and to continuously improve the process over time.

Introduction

Process control is commonly understood as an engineering discipline that deals with computer architecture and algorithms for controlling the output of a specific process. Digital computer control, which is linked to the availability of computers, was brought into the smelting industry in the early 1980s. The aims were and still are to maintain a process operating steadily under the designed specification conditions, achieve the desired quality of the product, and reduce cost through improving the efficiency of the process, while minimizing the human and systems error occurring in the process. However the potential to integrate the power of human reasoning and decision making with the almost unlimited computational capacity now available has not yet been explored. Furthermore, more advanced control concepts are needed in process control, rather than "fiddling" the parameters and/or compensatory actions.

As Taylor and Chen [1] pointed out, a more robust overall control model is required for industries, such as aluminium smelters, to meet the needs of energy reduction and environmental compliance [1]. Figure 1 shows a simple illustration of such a control model. However, only a fraction of this model can be observed in the current control practices in smelters. Compensatory actions, such as manipulating the input to reach the desired outcome temporarily, without an understanding of the variation, often occur. Many important elements in the control model are still missing. To fully implement this control model requires a higher level of system and human interaction.

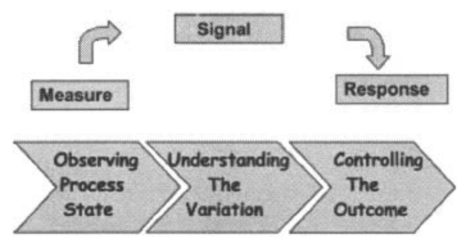

Figure 1: A simple model for the control process adapted from [1]

The aims of the present research are to explore the impact of human factors and decision making on process control as well as the interaction between the systems and human operators. Ultimately, the findings will be integrated into systems, which will improve current process operation and control practices, hence reduce the cost of production, energy consumption and the impact on the environment. The impact of human factors and decision making in process control is significant and pervades every aspect of the operation and control. This paper will use a few examples from Smelters A and B (names cannot be stated for confidentiality reasons) to demonstrate the impact of human factors and some of the missing elements in the current control practice in the aluminium smelting industry, as well as the methodology for potential improvement based on the model in Figure 1.

Observing process state – Measurements

Aluminium smelting is a multivariate process and involves highly complex mechanisms such as mass and energy balances, electrochemical reactions, supply of raw materials, and maintenance of the composition of the electrolyte [2]. The large amount of information coming in from such a process, some in real-time and others intermittently at varying frequency, is challenging for a human brain to process. This information consists of digital events and analogue signals and signatures sampled from the pots by the computer system, as well as the discrete manual measurements and visually observed signs or features Figure 1.

To control this complex process to achieve high productivity and efficiency requires day to day (and sometimes minute to minute) monitoring of the variables, and a high level of deductive problem solving and decision making skills using the process information as described above. However, in this information-rich environment, the absence of a strategic procedure or a system to manage the data, visual observations, and verbal communications, some of the valuable information is often diluted or even lost.

This is illustrated by the flow chart in Figure 2, which shows the common observations obtained from many modern smelters. Therefore, the efficiency and effectiveness of the operational staff's decision making or problem solving are made based on incomplete information and might not be optimal. Furthermore, implemented decisions cannot be easily tracked and followed up. This could have short term or long term impacts on the process and improvement. This indicates that the first phase in the control model in Figure 1 is not fully implemented in many smelters and it has negative impact on the process in the subsequent phases.

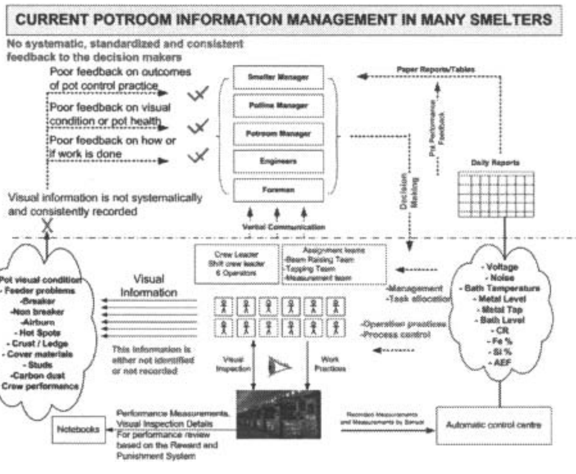

Figure 2: A flow chart illustrating the current information management situation in many smelters

Carbon Dust and Airburn

One example of the influence of human factors on process control and the consequence of making decisions based on incomplete information, (which is illustrated on the left of the flow chart in Figure 2) is the presence of excess carbon dust and airburn in Smelter A. When 80% of the pots in the reduction line have excess carbon dust and severe airburn, it is most likely that the carbon plant gets the blame for poor anode quality. That was the situation in Smelter A, until the external experts observed the operational and control practices in the potroom. It was diagnosed and identified that the carbon pieces floating between the anodes and cathode in the pots and the presence of carbon pieces in the bath material process circuit were the root causes of excess carbon dust and airburn. Without full information and the understanding of the cause and effect, the decision made to blame the anode quality (which is controlled by the carbon plant), and not to investigate the situation and take corrective actions, is in agreement with the illustration in Figure 2. It also shows the fact that the concept of the control model was also missing in the practice in this.

Improved Information Management

What has just been described is only one of the million cases which happen every day in smelters. It has been recognized that an advanced supervisory control system integrated with the robust control model would improve information management and process control by allowing the operators to observe the process with more meaningful information [1, 3]. Figure 3 shows the proposed improved information management model with the implementation of an advanced supervisory control system. This will allow the smelter information to be recorded and analysed systematically and consistently, and provide meaningful information to assist the operational staff to determine the process state.

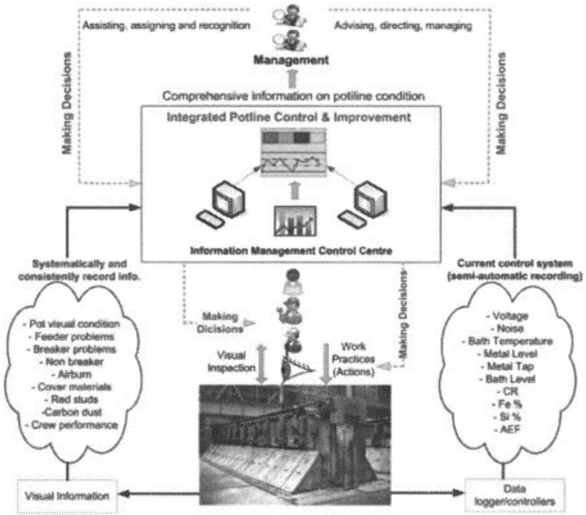

Figure 3: A flow chart illustrating a better information management model with the application of an advanced supervisory control system

Bath Level Control

One example demonstrating the effectiveness of a better designed supervisory system which is able to provide meaningful information to assist the operational staff on process decision making is a case study conducted of bath level control in Smelter A [3]. Low bath level has been a serious issue for this smelter. The percentage of the potline having bath level below the lower control limit every month in the previous two years ranged from 20% to 80%. The root cause was not found for a long time. Meanwhile, the impact of low bath level to the process was detrimental. Eventually it was identified by the external experts as problems with the supply of crushed bath materials. The crusher was broken down so often that the supply of crushed bath material for anode cover dressing was not reliable. Therefore, at times, there was no material to replenish the liquid bath. This root cause was simple and clear, but because of the missing links in the information management within the smelter, it was difficult for the operational staff to pinpoint.

There are 6 sections in the potline in Smelter A and the performance of the 6 sections were significantly different [3]. Even though the crushed material was not available for the whole potline, one of the sections managed to control the bath level within the control region consistently. It was found that the leader of this section used a newly implemented supervisory system to monitor the bath level situation, while the leaders of the other sections resisted the use of the new system and instead continued using printed daily reports with only numbers and tables. The new system incorporated some tools such as colour management of data, statistical graphs and pictorial illustrations for operation practice standard. The system was designed to be user friendly and took into account human factors such as perception of risk. For example the user will feel pressure and high level of risk when the measurements of the pots are highlighted in red (ie indicating it is outside the control region). By using the system, the section leader was aware of the bath level situation of the pots [3]. He asked the operators to tap the bath out of the pots which had high bath level and stored the bath material for anode cover material when the crushed bath material supply was not available. Furthermore, as a leader, he created a reward system to motivate the operators to do the daily operational and control tasks such as bath level control. The performance of this section demonstrates the impact of leadership, management and decision making skill on operation and process control.

Understanding the variation – Root Cause Diagnosis

As shown in the control model in Figure 1, understanding the variation links the observation of the process (ie. the stimulus, what you see) to controlling the outcome (ie. the response, what you do and achieve). Process variation is classified into three generic types: common cause or natural variation, special cause variation and structural cause variation [1]. Without the understanding of variation, the actions taken can often be compensatory or incorrect, thus the variation stays within the process persistently.

The case study of bath temperature control in Smelter B is an example which demonstrates the importance of understanding the variation and identifying the root cause [4]. Figure 4 shows the thermal cyclic situation observed from a pot. It shows that chemical additions were used to adjust bath temperature without diagnosing the root cause. Soda ash was added when bath temperature was low and outside the control specification box, and a large amount of AlF_3 was added to attempt to fix high bath temperature. The consequence was that the temperature cycled and this problem remained in the process. A statistical control tool (control ellipse) was then implemented to guide the operators to understand the variation and diagnose the root cause. The root cause of the continual temperature cycling was the inappropriate use of additions, while the root cause of some of the extreme high temperatures was due to alumina feeding problems [4]. This is a practical example of the implementation of 'understanding the variation' in the control model. A detailed representation of phases 2 and 3 of the control model is shown in Figure 5.

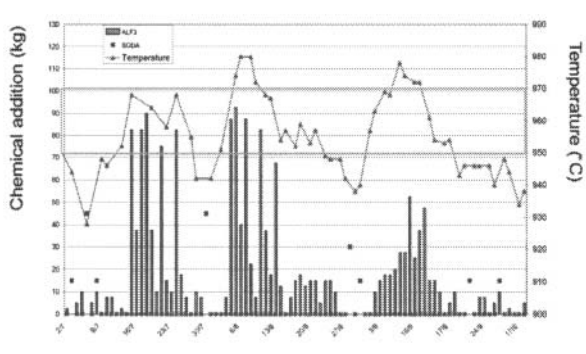

Figure 4: Temperature and chemical (AlF3 and soda) addition indicate the thermal cyclic situation of a pot

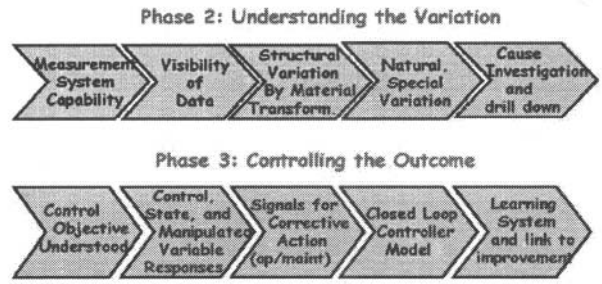

Figure 5: A more detailed representation for Phase 2 and 3 of the control model, adapted from [1]

Operators as Signal Detection Systems

However, as discussed previously, many of the current systems do not even provide complete information to the operators, and furthermore, most of these systems also do not have the ability to guide or assist the operators to understand the variation and identify the root cause. They rely heavily on the operators to make judgments and detect the process problems. In this case, the operators take on the role of signal detection systems for identifying problems. Figure 6 illustrates a basic signal detection system [5]. The input x (ie. process information) is a stimulus, and the stored 'database' is the memory of the operators. The box is the simplified decision making process for the operators to arrive at some function Z which is used to formulate a response based on some decision making criteria. However, without guidelines or the provision of technical constraints, this decision making process model gives the operators an un-reined degree of freedom. Coupled with the influence of a low level of situation awareness (due to incomplete information), perception bias, and selective attention, it can often lead to poor decision making [6, 7]. The consequence is that process abnormalities (special causes) are not identified and left un-attended. Thus such abnormalities keep recurring.

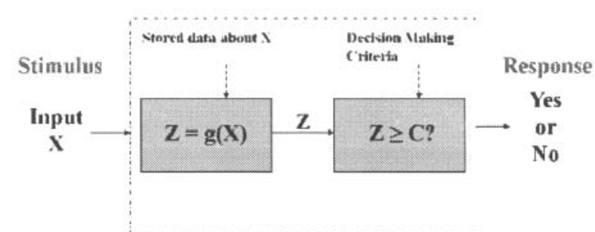

Figure 6: A basic signal detection system, redrawn from [5]

Improved Signal Detection System

As suggested by Taylor and Chen, with clear identification and classification of the three types of variation in phase 2 as given in Figure 5, an automatic control system incorporating a robust control model can be designed to assist the operators to not only observe the process but also to detect and diagnose the root cause of the process abnormalities. Figure 7 illustrates a model of automatic system and human operators working together on detecting process abnormalities. In this model, the system detects and classifies the process abnormalities and sends alarms to the operators. The operators then respond to the alarms by investigating the process and diagnosing the root cause. The overall performance is an improvement over the model in Figure 6 [5, 8, 8, 10, 11].

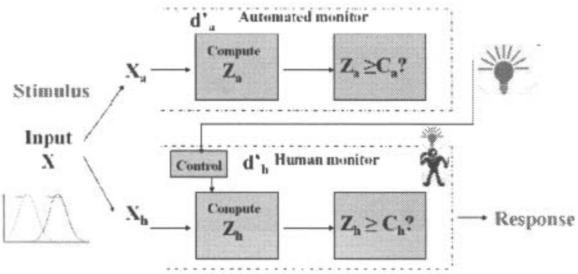

Figure 7: A detection model with system and human monitors, modified from [5]

Controlling the outcome - Response

Once a problem is detected by the system and confirmed by the operators, corrective actions are required as illustrated in phase 3 in Figure 5. Here, human operators can take immediate stabilizing actions to correct the immediate causes, such as removing anode spikes, cleaning the bath built up on the breaker or fixing the malfunctioning feeders. The operators can also implement a scientific problem solving methodology to lower the long term variability of the process [12]. The process of the scientific problem solving process is illustrated in Figure 8.

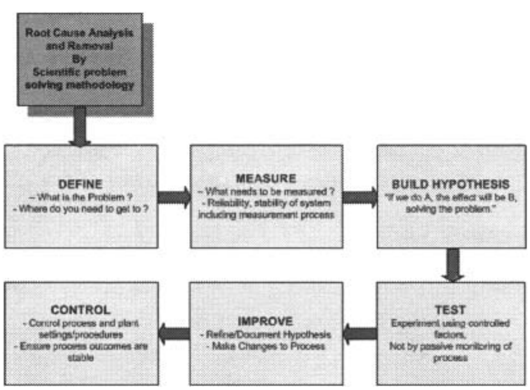

Figure 8: An illustration of the scientific problem solving methodology, adapted from [12]

Referring to the case study of bath temperature control in Smelter B described earlier, once the root cause was identified as an alumina feeding related issue and low metal level situation, the problem was DEFINED. The MEASURE was temperature. Therefore a 10-day response plan was implemented for the hot and sick pot (HYPOTHESIS BUILDING and TEST). The thermocouples were recalibrated and extra temperature and metal level measurements were taken every shift. The cathode was cleaned every day during anode changing. AlF_3 addition was maintained at a nominal rate. Along with other corrective actions, the temperature of the pot was brought down from 985 °C to 976 °C at the end of the plan (IMPROVE). A second plan was then implemented and this brought the temperature down and maintained at 960°C (CONTROL). This approach removed the root cause by the scientific problem solving methodology illustrated in Figure 8.

Every step in Figure 8 involves a large degree of human reasoning, thinking, decision making, and action taking as demonstrated in the example above. The outcomes and the learning from the process of problem identification, diagnosis and solution achieved should be stored in a system and carried on to be used in solving other problems. A well designed system will not only guide the human operators to implement the scientific methodology but also allow for feedback from the operators; hence a learning process takes place and the system can be continually improved. The system design should also take into account human perception, attention and situation awareness to avoid bias from individual experience or knowledge.

Conclusions

In conclusion, this paper demonstrates the importance of the control model and the influence of human factors to aluminium smelting process operation and control, by using actual examples from aluminium smelters. The examples have shown the influence of human factors in operation and control decision making. This shows that smelters urgently need an advanced system which incorporates scientific human reasoning functions, tools and guidelines to assist the operators to better observe the process, understand the variation, remove the root causes, and therefore better control the outcome.

References

1. M. P. Taylor and J. J. J. Chen, Advances in process control for aluminium smelters. *Materials and Manufacturing Processes*, 22(7):947–957, 2007
2. J. J. J. Chen and M. P. Taylor, Control of temperature and aluminium fluoride in aluminium reduction. *International Journal of Industry, Research and Applications*, 81:678–682, 2005
3. Y. Gao, M. P. Taylor, J. J. J. Chen, and M. J. Hautus, Operation decision making in aluminium smelters, *Engineering Psychology and Cognitive Ergonomics, Human - Computer Interaction International*, pages 167–178, 2009
4. Y. Gao, M. Gustafsson, M. P. Taylor, and J. J. J. Chen. The control ellipse as a decision making support tool to control temperature and aluminium fluoride in aluminium reduction, The *9th Australasian Aluminium Smelting Technology Conference and Workshop*, 2007
5. R. D. Sorkin and D. D. Woods, Systems with human monitors: A signal detection analysis. *Human-Computer Interaction*, 1:49–75, 1985
6. S. B. Most, D. J. Simons, B. J. Scholl, R. Jimenez, E. Clifford, & C. F. Chabris, How Not to Be Seen: The Contribution of Similarity and Selective Ignoring to Sustained Inattentional Blindness. *Psychological Science (Wiley-Blackwell), Wiley-Blackwell,* 2001, *12*, 9-17
7. J. A. Swets, & A. B. Kristofferson, ATTENTION, *Annual Review of Psychology, Annual Reviews Inc.*, 1970, *21*, 339-366
8. J. A. Swets, R. M. Dawes, and J. Monahan, Better decisions through science. *Scientific American*, 283(4):82–, October 2000
9. J.A. Swets. The science of choosing the right decision threshold in high-stakes diagnostics, *American Psychologist*, 47, No.4:522–532, April 1992
10. J.A. Swets, Robyn M. Dawes, and John Monahan, Psychophysical science can improve diagnostic decisions. *American Psychological Society*, 1, No. 1, 2000
11. J.A. Swets, David J. Getty, Ronald M. Pickett, and David Gonthier, System operator response to warning of danger: A

laboratory investigation of the effects of the predictive value of a warning on human response time. *Journal of Experiemental Psychology: Applied*, 1, No.1:19–33, 1995
12. M. P Taylor. Scientific problem solving: Getting to grips with complex problems in industry, level 2, lmrc smelter training course - reduction module