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METAL SCRAP RECYCLING 4.0: TOWARDS SMART OPERATION AND PRODUCTION OF HIGH-QUALITY ALLOYS

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Abstract— In the era of Industry 4.0, manufacturing systems are becoming more and more efficient. Indeed, decision making for operations and production enables companies to maximize their profits and be more competitive. However, some industries are behind in their integration of Industry 4.0 technologies. This is the case of foundries, which, with their traditional manufacturing processes, do not perceive the potential benefits of Industry 4.0. In particular, this industry relies on digital technologies to connect production systems throughout the supply chain with smart factories. The manufacturing industry must rely on Industry 4.0 to produce more personalized products while remaining economically competitive. Hence, this study seeks to optimize the manufacturing process of a titanium recycling and foundry company, Metalliage Inc., with a program that selects the raw materials to be melted in order to minimize costs and meet order constraints. A model is developed to simulate the production as a mixed integer linear programming problem. The conducted study shows a potential gain of 20% that could be achieved with production supported by Industry 4.0 technologies. A possible integration of these technologies will be proposed in the context of a metal recycling plant.

Keywords- Industry 4.0; Foundry 4.0; Smart Factory; Titanium recycling; Circular Manufacturing; Metal scrap

I. INTRODUCTION

A. Context

Ferrotitanium is usually produced by induction melting of titanium scrap with iron or steel [1]. However, it is also produced directly from titanium mineral concentrates. The standard grades of ferrotitanium are 30% and 70% titanium (Ti). During steelmaking, titanium is introduced as ferrotitanium because of its lower melting temperature and higher density compared to those of titanium scrap. Producers of interstitial-free, stainless, and high-strength low-alloy steels are the major consumers of titanium within the steel industry [2]. The main source for titanium recycling is currently titanium scrap produced by smelting and manufacturing processes instead of pure Ti products [3]. The main impurities in Ti scrap are oxygen (O) and iron (Fe). Ti scrap with low concentrations of O and Fe are remelted to obtain Ti and its alloys. On the other hand, Ti scrap with a high content of O and Fe is used as ferrotitanium. Given the increase in demand for Ti, the amount of low-grade Ti scrap generated will exceed the demand for ferrotitanium. Therefore, there is a need to improve the removal of O & Fe for the efficient use of Ti [4].

At the start of the 21st century, the recession forced many companies to cut production costs and better understand customer demand. Lean Manufacturing has shown itself to be a response to its new problems by manufacturers by reducing waste and actions without added value. Lean manufacturing is regularly defined as a complete set of techniques that help to constantly identify and eliminate waste (muda), improve quality and production and reduce time and costs. These include continuous process improvement (kaizen) and error protection (poka-yoke) [5]. Lean manufacturing has brought many tools, methodologies, concepts allowing an optimal production process. By following a Lean direction, any business in any industry of any size or type can continuously improve their business over the long term [6]. The Value Stream Mapping (VSM) methodology is a Lean manufacturing method used to improve the capacity of a production line. VSM can be used as a data-driven decision-making tool to identify constraints in the current state, to identify waste and to propose an optimized future state of production [7]. Lead times are reduced, the added-value ratio is significantly increased and cycle time is improved by minimizing handling time. For a long time, VSM was the tool to use to reveal all the data, problems, processes and operations to manufacture products [8].

Today, the industry is going through a period of technological progress, coined as Industry 4.0 [9], as a result of new digital industrial technologies. In Industry 4.0, sensors, machines, parts and computer systems will be connected along the entire value chain (e.g. deploying Internet-of-Things (IoT) [10]). These connected systems can interact with each other and analyse data to predict failure and adapt to change. In addition, plant operators can use IoT enabled devices to be better informed on process flows, operation and foundry process progress. Industry

4.0 will enable data collection and analysis, improving speed and flexibility to produce higher quality goods at reduced costs. This will increase productivity and support industrial growth consequently [9]. Companies have to start preparing for this fourth industrial revolution in order to remain competitive with competitors around the world. For example, production control systems using material consumption data could be deployed, forecasting the need for consumables by informing the relevant personnel in the company at any time. *Foundries 4.0* is the integration of Industry 4.0 principles into traditional foundries. There are many issues at stake: the casting process is known to be one of the most energy-intensive processes. Integrated sensors in an IoT architecture can be an effective way to reduce energy consumption in this industry resulting in a more sustainable manufacturing process. These technologies can enable better control of casting processes by measuring casting parameters in real time. Hence, we can easily understand how Industry 4.0 technologies can improve the metalworking industry [10]. However, the integration of digital technologies towards intelligent foundries is not yet well defined and explored to its full extent. There are many unknown aspects of this digital integration. It is therefore necessary to identify these stages in order to acquire an understanding of all the challenges and to ensure a smooth transition from foundries to Smart Foundries or *Foundries 4.0* [11]. Knowledge gained during the project on these *smart* approaches in this field can easily be transferred to other companies in the same field (e.g. metallic scrap recyclers, foundries, titanium alloy producers and metal industries as a whole), therefore contributing to increase competitiveness of the Canadian metal industry.

B. Case study: Metalliage Inc.

Metalliage is a company operating since 1998 in the Greater Montreal area with the objective of producing the highest quality titanium alloys in the market by recycling titanium scrap materials. Today, Metalliage supplies nearly four continents and twelve countries with these products. Metalliage Inc., as a major producer of ferrotitanium in North America, aims to develop a knowledge-based approach in their process improvement strategy. The company has developed valuable in-house expertise in controlling the casting process parameters, based on practiced standards, for various families of ferrotitanium grades. However, it is lacking specific expertise on automatization and operation research for plant and process-flow optimization and improvement in the context of Industry 4.0. In order to strengthen the leadership position of the company several research and development projects are envisioned enabling an increase of its efficiency and its market share. In this context, the presented study on Industry 4.0 technology integration towards a more sustainable and efficient foundry process flow was developed to optimize the production plant and its process flows.

The processes at Metalliage can be sub-divided in five divisions, listed as follows: 1) the material division, 2) the washing line., 3) the furnace, 4) the crushing and 5) the bagging. Titanium arrives at the plant as machining chips or scrap and passes through each of these departments. However, the flow of products between these divisions requires improvements, e.g. the location of the different machines and the location of stocks should be optimized for more efficient plant operation. The company plans have also evolved over the years and no updated data is available. Finally, the metallurgy industry is lagging behind Industry 4.0. The approach to moving towards smart factories in the case of foundries is still poorly researched and needs to be more concretely defined in order to remain competitive and efficient within the industry. A major research gap is a framework for integration of smart digital technologies towards intelligent foundries, which is not yet well defined and explored. Metalliage wishes to improve its production line in order to increase its market share, diversify its production and prepare its entry into a *smarter* approach, making use of modern automation, monitoring, tracking (communication) and controlling technology.

C. Objectives

The main objective of this research project is to investigate and propose solutions for the transition towards Industry 4.0 in the metallurgical industry. This includes optimization of the process flow and the manufacturing process for high value metal alloy production by scrap recycling through an Industry 4.0 approach using smart communication.

A preliminary study of the Metalliage production line with a VSM highlighted the foundry as the bottleneck station of the Metalliage production line. It is also the primary station because it is the stage that gives the most added-value to Metalliage products: it is the stage that transforms waste into a high-quality material that can be used again in industry.

The objective of this research is to propose a solution to optimize this key stage by automating the selection of raw materials in order to optimize the manufacturing cost. A decision-making tool will be created in mixed integer linear programming for this purpose. In a first step, the flows of the foundry station will be modeled, then a numerical example will validate this model. Finally, the impact of such an optimization tool will be calculated for real orders. Based on the results obtained, proposals will be made to achieve these efficiencies in practice and to justify investments to optimize the process with digital technologies. This work therefore presents an approach to realize the first steps towards Foundry 4.0 by proposing a method of process optimization using *smart technologies*.

II. Foundry optimization

A. Modelization

In order to improve the production line and more precisely the foundry station, it is necessary to model the material flows that describe this production. Ferrotitanium ingots of around 70% titanium correspond to the output of the system. As shown in Fig. 1, at the input, raw materials have different compositions and different shapes.

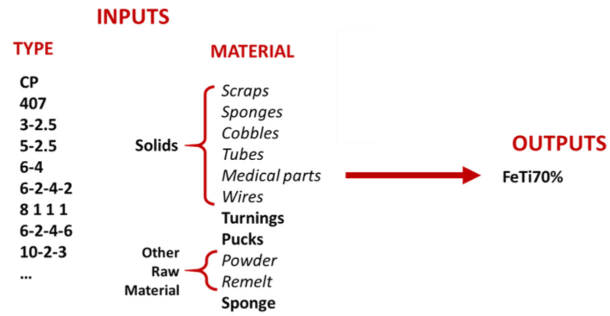

Figure 1. Production principle at Metalliage

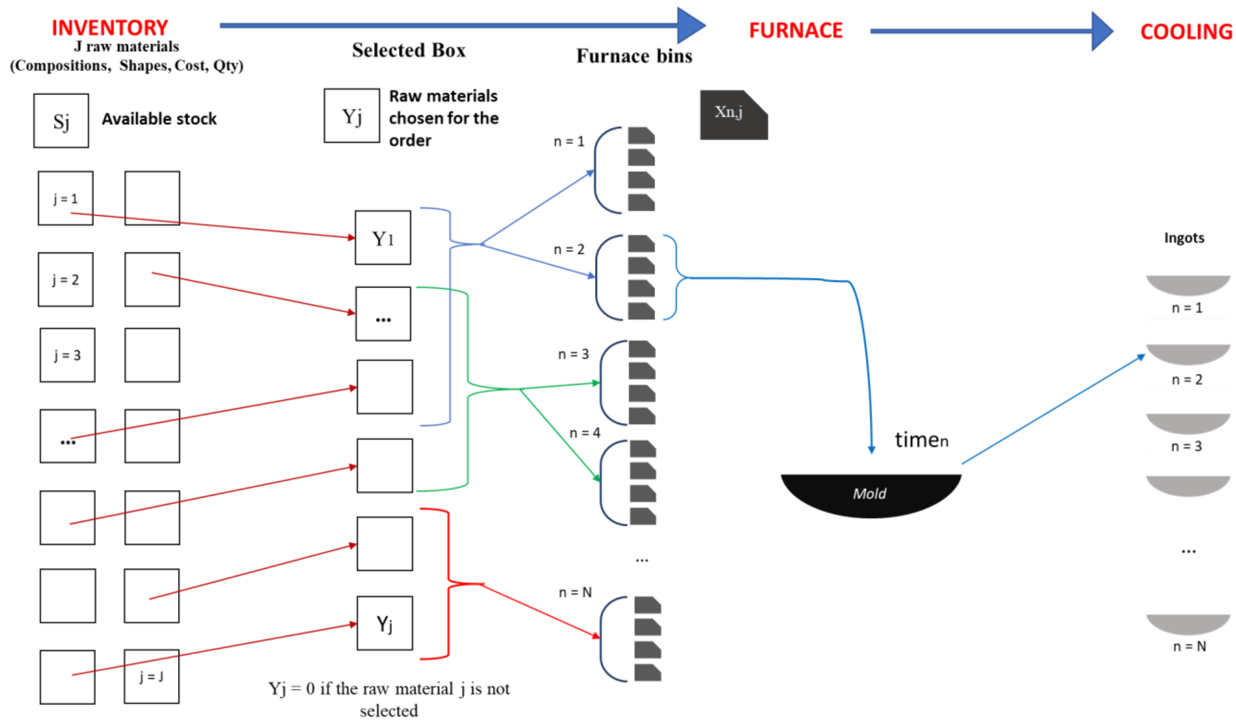

Figure 2. Developed model of the production line at Metalliage

TABLE I. INDICES, PARAMETERS AND VARIABLES

n	Ingot indice (n = 1...N)
j	Raw materials indice (j = 1...J)
a	Atom indice (a = 1...A)
Sj	Quantity of raw materials j in stock
Yj	Quantity of raw materials j used for manufacture
Xnj	Quantity of raw materials j used for the ingot n
Cja	Composition of the raw material j in atom a
ICna	Composition of the ingot n in atom a
DCna	Composition required by the customer in atom a
aj	1 if the raw material j has been used for the order, 0 otherwise
bnj	1 if the raw material j has been used for an ingot, 0 otherwise
rmcj	Raw material cost j /lbs
M	Ingot mass
m	Maximum amount of raw material *j* boxes per order
p	Maximum amount of bins per ingot in the furnace

More precisely, we select from the stock of raw materials available in quantity S_j, the quantities Y_j that we need to manufacture an order. These Y_j quantities are in boxes. The contents of these boxes will then be put in bins for the foundry. Each bin contains one type of raw material for the production of 1 ingot. The quantity of raw material in the bins is noted $X_{n,j}$. The mixing of the $X_{n,j}$ allows to obtain ingots respecting the atomic composition required by the customer of the order. This modeling is illustrated in Fig. 2. Table I shows the meanings of the different indices, variables and parameters in the model. Currently, the selection of raw materials and the composition of ingots is done manually thanks to the experience of the company's engineers. However, considering all the cost and composition parameters in order to determine the most optimal raw material choice is humanly impossible. The idea is to automate the selection of raw materials. Section *II. B.* will detail the equations that will govern this optimization program.

B. *Constraints*

After formulating the problem, we need to write the constraints that will drive the model. First, the composition $IC_{n,a}$ of each ingot n in atom a is given by the raw materials $X_{n,j}$ that were used to make this ingot.

$$IC_{n,a} = \sum_{a} \sum_{j} X_{n,j} . C_{j,a} \tag{1}$$

The raw materials $X_{n,j}$ put in the ingot come from the boxes of raw materials Y_j taken from stocks.

$$.Y_j = \sum_n X_{n,j} \text{ , } \forall j \tag{2}$$

From a quality point of view, all ingots must comply with the order. Table 2 is an example of the requested composition. It composes threshold values $DC_{n,a}$ which must not be exceeded. Thus, the compositions in atoms *a* of the ingots *j* of the ingots $IC_{n,a}$ must respect the following equations:

$$IC_{n,Ti} \geq DC_{n,Ti}, \forall n \tag{3}$$

$$IC_{n,a} \leq DC_{n,a}, \forall n, \forall a \geq 1 \tag{4}$$

The quantity of material j picked from stocks Y_j must not exceed the available quantity:

$$Y_j \leq S_j, \forall j \tag{5}$$

For logistical reasons, the number of boxes of raw materials collected should not be too large. A maximum amount *m* of boxes per order from stock is fixed for this purpose:

$$\sum_j a_j \leq m \tag{6}$$

Similarly, for logistical reasons, the number of bins of raw materials poured into the oven for each ingot should not be too large. A maximum amount *p* of bins per ingot in the furnace is defined for each ingot:

$$\sum_j b_{n,j} \leq p, \forall n \tag{7}$$

TABLE II. ORDER EXAMPLE

Analysis	element	Min	Max	RESULTS	element	Min	Max	RESULTS
	Ti	65.00%		69.83	Si		0.50%	0.12
	Al		3.00%	2.70	Sn		0.50%	0.04
	V		3.00%	1.49	P		0.05%	0.02
	N		0.40%	0.25	S		0.05%	0.02
	C		0.10%	0.10	Fe		30.00%	24.50
	Pb		0.03%	0.01				

The ingots have a mass of 1 ton, or approximately M = 2200 lbs:

$$\sum_j X_{n,j} = M, \forall n \tag{8}$$

C. *Objective Function*

With the constraints of our model defined, we seek to minimize the production costs of ferrotitanium ingots. The main production cost comes from the raw material used to manufacture the orders. The raw material cost *RMC* is defined by the sum of the costs of the different raw materials Y_j used:

$$RMC = \sum_j rmc_j . Y_j \tag{9}$$

The objective function is defined as:

$$MIN = RMC \tag{10}$$

D. *Numerical example*

A first test is performed with J = 30 raw materials from stock, i.e. a small part of the stock available at Metalliage. The program is asked for the raw materials to be taken from and poured into the furnace in order to obtain N = 2 ingots for the order in Table II. The resolution of the model is done with LINGO. The compositions of the ingots obtained are given in Table III. The program returns the values of Y_j and $X_{n,j}$ in Table IV. These compositions comply well with the requirements of the order. The raw material cost is $2,667 for these two ingots. In comparison, when these two ingots were manufactured by choosing the raw material without optimization, the raw material cost was $3,012. The cost of raw material is therefore lowered to satisfy the order, the model is therefore verified and helps the manufacturer to choose the raw materials optimally.

TABLE III. INGOT COMPOSITIONS (IN %)

	n=1	n=2
Ti	66.77	65.64
Al	2.41	2.91
V	1.11	1.20
N	0.86E-2	0.91E-02
C	0.93E-01	0.99e-01
Si	0.82E-01	0.82-e01
Sn	0.36	0.45
P	0.11E-01	0.11E-01
S	0.11E-02	0.11E-02
Fe	27.10	27.09

TABLE IV. RAW MATERIALS SELECTED FROM STOCKS AND CONTENTS OF FOUNDRY BINS (IN HUNDRED OF LBS)

	Yj	$X_{n,j}$ n=1	n=2
J=1	12	6	6
J=2	0	0	0
J=3	8	4	4
J=4	0	0	0
J=5	0	0	0
J=6	0	0	0
J=7	9	4	5
J=8	0	0	0
J=9	0	0	0
J=10	0	0	0
J=11	6	5	1
J=12	0	0	0
J=13	0	0	0
J=14	0	0	0
J=15	0	0	0
J=16	0	0	0
J=17	0	0	0
J=18	0	0	0
J=19	0	0	0
J=20	0	0	0
J=21	0	0	0
J=22	0	0	0
J=23	0	0	0
J=24	0	0	0
J=25	0	0	0
J=26	0	0	0
J=27	9	3	6
J=28	0	0	0
J=29	0	0	0
J=30	0	0	0

III. RESULTS

The objective now is to see the gain possible with this tool in conditions similar to the manufacturing reality with a real control. Here an order of $N = 20$ ingots will be taken. For the order of Table 2, the production obtained in reality had the composition shown in Table V.

The cost of this production was $33,664. The composition obtained from the optimization program and the production price are now being examined. J = 167 different raw materials that were available in Metalliage's inventory at the time the order was actually produced. There is also a maximum number of boxes of raw materials at m = 10. The composition is given in Table VI: the customer's restrictions are respected.

TABLE V. AVERAGE COMPOSITIONS OF INGOTS MANUFACTURED (IN %)

TI	69.83
AL	2.70
V	1.49
N	0.25
C	0.12
SI	0.12
SN	0.06
P	0.02
S	0.02
FE	24.50

TABLE VI. AVERAGE COMPOSITIONS OF THE INGOTS OBTAINED WITH THE OPTIMIZATION PROGRAM (IN %)

TI	65.09
AL	1.36
V	0.71
N	0.01
C	0.09
SI	0.09
SN	0.00
P	0.01
S	0.01
FE	29.94

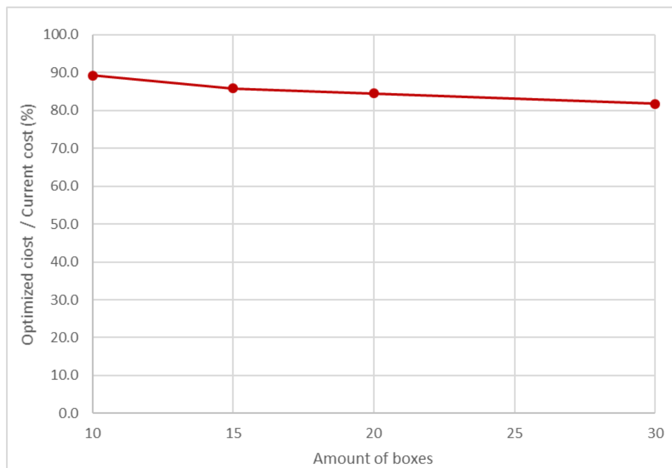

Figure 3. Evolution of the production cost for different amounts of used distinct raw materials

The cost of such production was $30,034, an 11% decrease in production cost. We then look at the evolution of the cost by allowing ourselves to use more different raw materials. This evolution (cost reduction) is visible in Fig. 3, which presents the ratio of optimized cost over the current costs versus the amount of raw material boxes. The results for a larger number of boxes of raw materials are not studied because the intention is to stay in ranges feasible for the operators. More raw materials would further reduce production costs. Indeed, more boxes of raw materials would reduce production costs by up to 19% because smaller batch stocks could be used to adjust blends. It would be essential to enable operators, especially forklift drivers, to increase their speed of execution in picking up boxes of raw materials from stock and preparing the bins for the foundry. The addition of floor markings, an inventory storage and labelling system would therefore be of considerable value in increasing productivity. A better communication of the actions and raw materials to be picked up would also improve this rate. The implementation of such an automation system would require additional precision in the composition of the raw materials poured into the furnace. It would therefore be interesting to find a system to identify the composition precisely at the time of receipt and to automatically update this composition in the inventory if there is a discrepancy indicated with the composition given by the supplier. A system that would allow checking the homogeneity of the composition of a batch of raw materials received would also be useful.

IV. Conclusion and Outlook

The study of the Metalliage production line revealed a lack of automation in the production of ingots in order to limit the cost of raw materials. This lack of automation is above all at the level of decision making in the choice of raw materials. Indeed, this is done manually and this is not the best choice for a production that optimizes profit. To fill this lack, a mixed integer linear programming tool has been developed to improve the selection of raw materials. It would be possible to reduce raw material costs by almost 19% thanks to an optimal selection of raw materials. In order to achieve these productivity and cost gains, several projects should be done in the future to achieve the transition to *Foundry 4.0* and the *Smart Factory*:

First, automate raw material selection to reduce production costs, for both raw materials and manufacturing, and to increase productivity. To achieve this goal, an optimization program that would propose raw material mixtures in an acceptable time frame (using an Artificial Intelligence algorithm requiring training data) should be proposed. A collection of data concerning the manufacture of ferrotitanium ingots at the foundry level, and more precisely at the level of the foundry time and the compositions obtained would also be necessary. Indeed, the shape of the raw materials swells during the casting time. This correlation could be done by analyzing the foundry data.

This optimization in the selection of raw materials and in the preparation of the blends requires an increase in the activity of the forklift drivers. An accurate determination of the composition of the raw materials received would also be important. In order to achieve these objectives, it would be interesting to rethink the inventory storage system to allow drivers to quickly access all the raw materials in the inventory. Implementing a 5S system in the warehouse would be helpful: floor markings would help keep workers safe and the workspace organized. It would be important to tidy the warehouse and remove all unused items from the work areas. This tidying should also take place in the offices, not just the shop floor. A labeling system that accommodates the variety of packaging of incoming raw materials would make it easy to identify raw materials for retrieval and avoid errors. An application could be developed that would indicate on a screen the raw materials to be taken from the stock, the contents of the foundry bins to be prepared, etc. In addition, a system that would alert smelters and forklift drivers when an ingot has finished melting would optimize the use of the furnace by minimizing ingot transition time. Finally, the increase in furnace filling speed would be important. Several solutions are possible. The furnace ramp could be designed to accommodate more of the different raw materials, or a crusher that would make the raw materials more uniform in shape could be considered.

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