APPLICATION OF OPTIMIZATION PROBLEM IN THE SELECTION OF FURNACE MATERIALS FOR ALLOY STEEL SMELTING

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ABSTRACT

In recent years, optimization methods have been widely and effectively applied in economics, engineering, transportation, information technology, and many other scientific disciplines. This article will systematize a real-life model that needs the help of Mathematics to solve production cost problems in business to clarify the relationship between Mathematics and practice.

Keyword: *Optimization, Optimal, Mathematical model, Alloy steel smelting.*

1. INTRODUCTION

Currently, the direction of scientific research to serve practice and solve problems arising in practice is of great interest. One of the most interested directions is the field of mathematical optimization [1-19]. When planning production and design based on optimization principles, it will save costs in terms of capital, raw materials, time and labor while increasing efficiency, productivity and quality of work. Therefore, the problem is to model real-world problems into optimization problems. Then, the results of the optimization problem will give us the most reasonable production plan in practice.

2. OPTIMIZATION PROBLEM

The general optimization problem is stated as follows:
Maximum (minimum) the function $f(x)$ with conditions:

$$g_i(x) \le b_i,\ i = \overline{1,m} \tag{1}$$

$$x \in X \subset R^n . \tag{2}$$

Inequalities in the system (1) can be replaced by equality or inequality in the opposite direction.
Then, the function $f(x)$ is called the objective function, the functions $g_i(x)$ are called the binding function. Each inequality (or equality) in the system (1) is called a binding.
Domain D = $\left\{ x \in X \,|\, g_i(x) \le b_i, i = \overline{1,m} \right\}$ is called the bound domain (or acceptable domain). Each $x \in D$ is called an alternative (or an acceptable solution). An option $x^* \in D$ is the maximum (or minimum) of the objective function, it means:

$$f(x^*) \ge f(x), \forall x \in D \text{ (with the problem of maximization)}$$

$$f(x^*) \le f(x), \forall x \in D \text{ (with the problem of minimization)}$$

is called the optimal solution. Then the value of $f(x^*)$ is called the optimal value of the problem. Solving an optimization problem is finding the optimal solution x^*.

Optimization problems (are known as mathematical programming) are divided into several categories: Linear programming (the objective function and the constraint functions are linear), nonlinear programming (the objective function and the constraint functions, at least one function is nonlinear), dynamical programming (Objects are considered as multi-stage processes) …. Optimization theory has given many methods to find the optimal solution depending on each problem. However, Linear programming is a problem that is fully studied in both theory and practice because: simple linear model to be able to apply, many other programming problems (original programming, nonlinear programming) can be approximated with high accuracy by a series of linear programming problems.

3. MAINT CONTENT

Determining the optimal furnace material composition for alloy steelmaking is a relatively complicated problem for two reasons:

+ The first, when smelting steel, the furnace materials do not enter the furnace immediately, but in stages. So, if we use different methods of distributing furnace materials in each stage, it will produce steel of different values.

+ Second, kiln consumption is actually determined by various parameters of the technological process. Those parameters are the volume of oxygen put into the furnace, the rate of oxygen introduced, the temperature of the smelting tank, the composition of the ore …

The rational choice of composition whether such an oven will lead to the selection of the optimal cooking technology. Because the problem is complex, we will make the following suitable assumptions for simplification:

Anticipate several smelting technology processes distinguished by basic process parameters that affect the composition of the furnace material.

There are 3 stages of the process that requires feeding: basic stacking, reduction, and refining.

For each embodiment of the technological process, by methods of linear programming, we can calculate whether the optimal furnace.

So now, we consider the kiln selection model for a fixed solution of the technological process. And we still consider the problem of cooking alloy steel from inherent steel, cooking from separate furnace materials in separate stages of the technological process.

We sign:

+ x_{ij} is the number of parts of steel made from the j-th furnace material ($j = 1..n$) put into the furnace at the i-th stage of the process ($i = 1, 2, 3$ - because according to above, we are assuming to consider 3 processes) .

+ $a_{ij}^{(s)}$ is the percentage of the s-th prime (elements: chromium, silicon …) not in steel for the j-th furnace material and i-th stage of the process , $s = 1..r$.

+ $a^{(s)}$ is the maximum allowable percentage of the s-th element in the finished steel, $s = 1..r$. Therefore $\sum_{i=1}^{3}\left(\sum_{j=1}^{n} a_{ij}^{(s)} x_{ij}\right) \le a^{(s)}$, $s = 1..r$.

+ $\underline{a_i}^{(s)}$; $\overline{a_i}^{(s)}$ is the minimum value, the maximum value of the allowable percentage of the s-th element in the i-th stage of the process. That is, then we have the condition : $\underline{a_i}^{(s)} \le \sum_{j=1}^{n} a_i^{(s)} x_{ij} \le \overline{a_i}^{(s)}$, $s = 1..r$, $i = 1, 2, 3$.

+ d_j is the reserve of whether the j-th furnace material, $j = 1..n$. Thus, the total number of parts of steel cooked from the j-th furnace material ($j = 1..n$) put into the furnace in all three stages must not exceed d_j , That is, we need the following condition to be satisfied: $\sum_{i=1}^{3} x_{ij} \le d_j$

+ c_{ij} is the cost per ton of alloy steel that can be obtained from the j-th furnace material ($j = 1..n$) put into the furnace at the i-th stage of the process (assuming that $\sum_{i=1}^{3}\left(\sum_{j=1}^{n} x_{ij}\right) = 1$). Then the total cost that the factory needs to spend is $\sum_{i=1}^{3}\left(\sum_{j=1}^{n} c_{ij} x_{ij}\right)$.

The real problem: "with a fixed plan of the technological process, let’s choose the furnace raw materials so that the factory spends the smallest cost while still ensuring the requirements of the technology" will be modeled as the following linear programming problem:

Determine the values x_{ij} so that

$$\begin{cases} \sum_{i=1}^{3}\left(\sum_{j=1}^{n} c_{ij} x_{ij}\right) \to \min & (3) \\ \sum_{i=1}^{3}\left(\sum_{j=1}^{n} x_{ij}\right) = 1 & (4) \end{cases}$$

Satisfy the conditions

$$\begin{cases} a_i^{(s)} \le \sum_{j=1}^{n} a_i^{(s)} x_{ij} \le \overline{a_i}^{(s)}, s = 1..r \ ; \ i = 1,2,3 & (5) \\ \sum_{i=1}^{3}\left(\sum_{j=1}^{n} a_{ij}^{(s)} x_{ij}\right) \le a^{(s)}, \ s = 1..r & (6) \\ \sum_{i=1}^{3} x_{ij} \le d_j, \ j = 1..n & (7) \\ x_{ij} \ge 0 \ , i = 1,2,3 \ ; \ j = 1..n & (8) \end{cases}$$

in there (5) are the technological conditions related to the chemical composition of steelmaking at particular stages of the process, (6) are constraints on the chemical composition of the finished product, (7) is the reserve constraint of the furnace material.

4. CONCLUSIONS

The paper presents a method application of the optimization problem for the selection of furnace materials for alloy steel smelting. This further elucidates the two-way intimate relationship between mathematics and practice and the important role of mathematics in practice. In the future, the author's follow-up studies will carry out research on optimization for the processes occurring in the engineering process.

5. ACKNOWLEDGEMENT

This work was supported by Thai Nguyen University of Technology, Vietnam.

6. REFERENCES

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