Steel Scrap Purchasing Optimization and Supply Management

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Abstract
A mixed integer non-linear optimization problem has been developed to aid in purchasing scrap steel. The model, which includes about 600 real-valued variables, 200 integers, and over 800 possible constraint equations, uses industrial data, actual market prices and supplier information to perform calculations. Prices, quality and supplier information are input or read into the model, along with selections of constraints and a production plan. The model has been in use by production personnel. To date, the case-by-case solution of the optimization problem has led to suggestions for improved steel blends and has indicated a potential for savings in monthly scrap purchases.

Introduction
The production of steel is dominated by the use of iron ore and recycled steel scrap. Recycled steel scrap is available on the open market as a commodity. The scrap commodity is purchased periodically to ensure that overall production targets are met. Recycled steel scrap is used primarily in electric arc furnaces (EAF) where it is blended and melted, batch-wise, to produce steel that is cast into solid shapes that are then rolled, treated, and shipped to customers. Producing families of steel grades with recycled steel scrap to meet customer requirements in a timely fashion is a key aspect of EAF operation.

Purchased steel scrap is the most important feedstock material for an EAF, contributing significantly to production costs. Steel scrap can be used in different proportions to achieve desired physical and chemical properties of the finished product in order to meet customer requirements. The economical use of recycled steel scrap is governed by many factors including the prevailing market price and availability from each scrap supplier (e.g. cars vs. refrigerators) and the content of constituents such as copper, tin, sulfur and phosphorus. Limiting or controlling the level of these constituents is of primary concern to meet requirements such as hardness and weldability and to ensure that steel material properties are uniform across the cast piece. Since the price and quality of purchased scrap fluctuate, a periodic adjustment is required to the relative usage rate for each batch of steel made in a particular period of time. The determination of the steel scrap usage rates results in an optimization programming problem that seeks to minimize scrap purchase costs plus operating costs. Figure 1 shows that the solution of the programming problem should indicate which scrap supplier to purchase from, what scrap type to use, and in what lot quantities, in order to fill customer orders and to maintain desired inventory levels for the steel producer.

Model Description

An approximate cost equation can be developed for optimization by considering cost of steel scrap and the cost of electrical energy used to melt it in an EAF. The cost of scrap is directly related to market pricing and availability as well as internal inventory holding costs. Market prices are determined through monthly negotiations with local scrap suppliers. Internal inventory holding costs for a particular commodity like shredded scrap account for the opportunity costs of purchasing a similar commodity on the open market. Energy costs are focused on approximating the electricity use for each scrap type. Electricity use will vary with the quality of the scrap type, its density and how it was prepared by the supplier prior to its use in an EAF.

Purchase costs and energy use costs can be related to the amounts of scrap used through Equation (1). The expression in Equation (1) is the economic objective function for the scrap blending optimization problem and is an estimate of the total operating cost c [$]. The purchase cost c_p [$] in Equation (1) includes the costs incurred for adding m [kg] of each scrap type i to an EAF batch j to meet production demand. In addition to the amount of scrap added to each batch produced, the cost c_p is related to the amount of scrap purchased from a particular supplier, the amount taken from inventory, and the integer decision variables used to choose the source and the pricing option for the scrap.

$$c = \sum_{i=1}^{I}\sum_{j=1}^{J}(c_{p_{ij}}) + \sum_{j=1}^{J}(c_e \times y_j) \tag{1}$$

The energy cost term is calculated by multiplying the energy use y [kWh] by the market price for electricity c_e [$/kWh]. The energy costs are computed for each of the J batches (heats). Each batch of steel produced requires its own addition of each of the I scrap types. The total number of batches J is set manually prior to optimization and the number I of available commodity types is also known for a selected time frame for a particular scrap purchase (i.e. one month). Cost is minimized by choosing the I×J scrap additions for the purchase period and the amounts to be purchased from suppliers.

The electricity consumption y for each batch j=1,..,J is modeled via a PLS-based regression equation. The amount of electricity used is formulated by developing the relationship between the I scrap commodities and operating variables q, such as additions of chemical reagents and temperature settings. The production variables q are set as constants for each optimization run based on knowledge of each steel batch type. Models such as the one shown in Equation (2) can be fitted using historical data available from production data bases. Other consumables can be modeled in a similar fashion as well [Sandberg, 2005].

$$y_j = \beta_0 + \beta_1 m_{1j} + \ldots + \beta_I m_{Ij} + \beta_{I+1} q_{1j} + \ldots + \beta_{I+Q} q_{Qj} \tag{2}$$

To meet customer demands for steel properties, quality constraints need to be met for each of n=1,…,N attributes α_{ni}, such as scrap density and concentration of trace metals (e.g. chromium and nickel), for each batch that is produced. Each type of steel scrap added to the batch will have different quality attributes that impact the batch quality according to the amount of scrap used. In particular, density is an important attribute since it is related to the throughput of the furnace. Density is computed using a bulk relationship that is related to packing of steel in a container vessel, thus, scrap steel of the same or similar elemental content will have very different densities if it is shipped shredded or un-shredded by the scrap supplier. Constraints for properties such as these can be modeled as the bounds shown in Equation (3). Equation (3) shows upper and lower bounds on a weighted averaged property that is computed using a mass fraction r_{ij} for a particular blend. The mass fraction provides a weight that adjusts the blended batch property according to the mass of scrap added to the batch.

$$LB_{nj} \le \left[\sum_{i=1}^{I} (\alpha_{ni} \times r_{ij}) \right]_{nj} \le UB_{nj} \quad , \quad r_{ij} = \frac{m_{ij}}{\sum_{i=1}^{I} m_{ij}} \tag{3}$$

For some elements, such as copper, the probability of exceeding the constraints in Equation (3) needs to be controlled carefully due to customer demands. To ensure that variability in the quality of the delivered scrap does not force a constraint violation during actual production, a 'back-off' is computed for the k=1,…,K important residual metals using the propagation of errors method of estimating variances, σ^2, for the weight averaged blended property p_k, (e.g. copper concentration) of the liquid steel. This is done via Equation (4). According to Equation (4), the estimated variance will change with the amount of scrap added to a particular batch at each computational step during numerical solution. An estimate of variance using Equation (4) ignores the multivariate interactions among changing properties of a particular steel scrap. This simplification allows for a smaller computational burden in solving the optimization problem numerically.

$$\sigma_{kj}^2 (p_{kj}) = \left[\sum_{i=1}^{I} (\sigma_{ki}^2 (\alpha_{ki}) \times r_{ij}^2) \right] \quad , \quad p_{kj} = \left[\sum_{i=1}^{I} (\alpha_{ki} \times r_{ij}) \right] \tag{4}$$

Using this variance estimate and the blended property mean, taken to be p_{kj} in Equation (4), the inverse normal distribution can be used to calculate a critical value z_{ckj} [Zhang, et al, 2002]. The critical value $z_{ckj} \rangle p_{kj}$ is chosen to meet a specific upper tail probability. This ensures that the upper quality bound will be in the right tail of the distribution of the blended property which should result in a lower rate of constraint violations in production. Under the normality assumption the rate of blended property bound violations is expected to be equal to the chosen tail probability level. The constraint for limiting important residual metals like copper then becomes $z_{ckj} \le UB_{kj}$ for these K critical properties.

To meet production demands, the m_{ij} scrap additions must be provided by selected suppliers. Certain suppliers of scrap steel sell at price levels that vary with the amount of scrap purchased for steel production. These price levels (tiers) can be modeled by introducing additional decision variables for a particular supplier [Heipcke, 2005]. In this formulation the decision variables m_a, m_b, and m_c represent the amount [kg] of scrap purchased at cost [\$/kg] c_a, c_b, c_c. Scrap can not be purchased at cost c_b until the maximum amount available at cost c_a has been purchased. If the amounts [kg] that define these price levels are B_a, B_b, and B_c then the following set of expressions can be applied for each supplier that has tiered pricing t=1,…,T.

$$
\begin{aligned}
& B_a \cdot b_b \le m_a \le B_a \cdot b_a \\
& (B_b - B_a) \cdot b_c \le m_b \le (B_b - B_a) \cdot b_b \\
& m_c \le (B_c - B_b) \cdot b_c \\
& b_a \ge b_b \ge b_c
\end{aligned}
\tag{5}
$$

In Equation (5) the decision variables b_a, b_b, and b_c are integer [0,1]. If scrap is purchased at say the price range b then b_a=b_b=1 and m_a is set to B_a. If b_b=0 then m_b=0 and if b_b=1 m_b is limited to the maximum amount B_b, and if b_c=0 then m_c=0. The expression $b_a \ge b_b \ge b_c$ ensures that purchases are made at higher tiers only when the tiers below have been used. The total scrap purchased from a supplier is then $m_t =(m_a + m_b + m_c)_t$, and the total cost [$] of the purchase is $c_t=(c_a \cdot m_a + c_b \cdot m_b + c_c \cdot m_c)_t$. The list of expressions in Equation (5) can be expanded for cases where suppliers have more than three tiers for some scrap types.

If a supplier does not use tiered pricing, then the total purchased amount [kg] is m_s, s=1,…S, and the associated cost [$] is c_s. Inventory can be treated as a supply source that provides scrap m_u, u=1,…,U, at a specific internal holding cost c_u. Equations (6) and (7) are then computed for each scrap type i=1…I. to calculate the total amount of each scrap type added to the EAF furnace and the associated cost of purchasing the scrap. Typically each of the sources of scrap supply whether tiered, single un-tiered, or internal inventory (T+S+U) can provide various scrap types to meet demand for producing blended recipes by replenishing each scrap type i=1,…I. The supply of scrap can therefore be equated to the demand for each scrap type through the key constraint in Equation (6). Total costs [$] for purchasing each scrap type are then given in Equation (7). This cost is used in the objective function shown in Equation (1). It is the sum of the costs incurred in purchasing scrap using various suppliers and price points.

$$
\sum_{j=1}^{J} m_{ij} = \sum_{t=1}^{T} m_{it} + \sum_{s=1}^{S} m_{is} + \sum_{u=1}^{U} m_{iu} \tag{6}
$$

$$
\sum_{j=1}^{J} c_{p_{ij}} = \sum_{t=1}^{T} c_{it} + \sum_{s=1}^{S} c_{is} + \sum_{u=1}^{U} c_{iu} \tag{7}
$$

If needed, bounds can be used to limit the amounts of scrap type added to each blend according to production requirements of supplier availability limits. Fixed amounts that must be purchased according to contractual obligations can be modeled by setting upper and lower bounds equal for the particular scrap type provided by a selected supplier.

Results

The model equations were programmed in a spreadsheet using a commercially available SQP-based solver software add-in, to minimize costs. The format chosen for this implementation allowed rapid development of the model. The model, as implemented in the spreadsheet, has fostered an improved method of making the monthly purchasing decision by allowing hands-on what-if studies to be done quickly. The studies are performed by specifying which batch recipes should be made during a month, by altering recipes while meeting steel grade requirements, and by verifying assumptions regarding the impact of adding more or less of certain scrap types to the furnace. Data integrity checking that was coded for the spreadsheet tool has provided an important benefit in that best guesses provided by experts regarding which constraints are binding can be verified easily.

Although the model has been in use for a short time, this work has resulted in attractive projected cost savings estimates over three months of use. This result is encouraging; however, it is tempered by the at times strong market fluctuations in scrap prices that have a large impact on the available benefits that can be extracted through an optimization system such as this.

References

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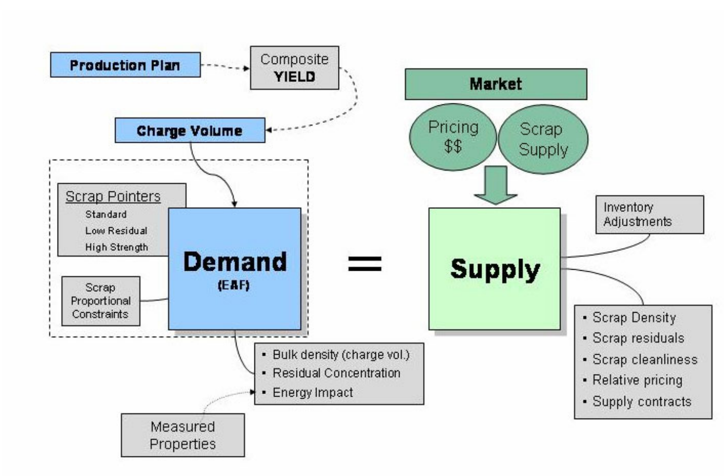

Figure 1: Scrap Purchasing Overview