A STUDY OF ROLLING-MILL PRODUCTIVITY UTILIZING A STATISTICALLY DESIGNED SIMULATION EXPERIMENT

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ABSTRACT

A statistically designed experiment was conducted to quantitatively describe the effects of operating conditions on rolling-mill performance. Instead of observing the actual performance of the facility, a Monte Carlo model was developed and used to simulate the operation of the mill under all the treatment combinations required to complete the experimental design. The empirical equations that resulted from the analysis of the simulated responses have proved useful in aiding mill scheduling, locating bottlenecks, determining economical operating strategies, and evaluating the potential of proposed operating changes.

INTRODUCTION

One of the key facilities in an integrated steel plant is a primary rolling mill. This facility receives ingots from the steel-producing facility and converts them to shapes that are suitable for final processing by other more specialized rolling mills.

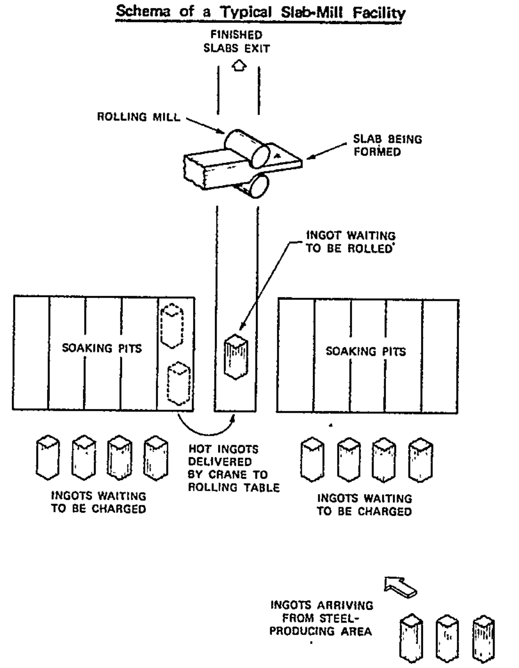
Briefly, a slab mill facility consists of two main components, Figure 1. First, there is the rolling mill, which shapes the ingot into the desired slab size. Second, there are soaking pits in which ingots, arriving from the steel-producing furnaces, are placed before rolling. Besides raising the ingots to a suitable rolling temperature and ensuring that the ingots are properly soaked through at this temperature, the pits also serve as a reservoir for the rolling mill and provide a continuous supply of ingots for the rolling operation.

The question which initiated this study was an obvious one: How to get more tonnage through a slab mill?

Therefore, consideration was given to a variety of factors thought to be limiting the production. Modifications to many of these individual operating factors had been tried with varying degrees of success.

Because of the many interdependent activities in the operation of a slab mill, because of the alternative operating strategies possible, because of the random occurrence of delays and equipment failures, and because of the irregular delivery of steel ingots, a computer simulation model of the facility was

FIGURE 1
Schema of a Typical Slab-Mill Facility



required to gain a complete understanding of the operation.

The model was written in GASP.[1] Data reflecting a slab mill's operation were collected to estimate parameters of necessary frequency distributions, such as ingot arrival rate, frequency and types of delays encountered, slab-mill rolling rates, and operating strategies. Once the model was developed, data from another operating period were collected and used to verify the computer model.

The simulation model was then used to conduct an experiment "at a slab mill."

1. PARAMETERS STUDIED

OPERATING, OR INDEPENDENT VARIABLES

Nine operating factors, thought to have an effect on the operation of a mill, were identified. They fell into three general categories: those which changed either the rolling operation, the soaking-pit operation, or the product mix that had to be processed by the facility. The nine and their regions of experimental interest were as follows:

(1) The number of scheduled operating turns studied varied from 14 to 20 per week. These were 8-hour shifts with no provision for overtime. A typical weekly arrangement for each number of turns was established.

(2) During scheduled rolling periods, minor rolling-mill operating problems can occur. The effect of unscheduled rolling delays, ranging from 5 to 20 percent of scheduled operating time, was studied.

(3) The rolling rate, defined as the number of slab tons produced per minute, was varied between 8 and 10. In practice, this value can be controlled (for example, by altering the rolling practices, or improving coordination between the mill and soaking pits so that a different number of ingots is delivered to the mill).

(4) The number of soaking pits investigated in the experiment ranged from the existing number to eight additional pits. This permitted an evaluation of the benefits of additional capacity, an alternative being considered at the time.

(5) The amount of unscheduled soaking-pit downtime, or maintenance time, was varied from 5 to 15 percent of the total time.

(6) The ingot tonnage that was delivered for processing ranged from a base level to 20,000 tons per week additional tonnage. The upper end of the range represented higher tonnages that were being anticipated, but had not been processed before.

(7) The transit time of the steel is the number of hours elapsed between the time that the steel is poured into ingots and the time they are placed in the soaking pit. As the transit time increases, and the steel cools, the soaking-pit residence time must be increased before the rolling temperature is reached. Standard transit times differ depending on ingot size and ingot type. The transit-time variable that was considered in the study was the average deviation in transit time relative to the standard times. The effect of average deviations up to 1.5 hours in excess of standard time, (that is, deliveries arriving 1-1/2 hours late) was investigated.

(8) For various reasons, the plant at times must put ingots into inventory. This cold-steel tonnage is worked through the system at a later time. Since relatively long heating times are required for cold steel, this puts an extra burden on the soaking pits. The effect of cold steel on the performance of the mill was studied by varying it from 0 to 20 percent of the total delivered tonnage.

(9) Certain grades of steel must be poured into special types of ingots called hot tops. Increasing Hot-top tonnage places an extra burden on the system because these ingots receive additional processing before reaching the slab mill. This results in a longer standard transit time and, therefore, in longer required pit residence time.

PERFORMANCE, OR DEPENDENT, VARIABLES

The performance of the operation of the facility was characterized by nine parameters:

(1) The weekly slab tonnage produced gave a measure of actual throughput. Note that when this figure is compared with the tonnage delivered, nominal 80 percent yield is considered.

(2) Any steel that is delivered to the slab mill, but cannot be processed by it, is set aside in inventory. This tonnage diverted is a measure of the inability of the facility to cope with the demand being placed on it.

(3) At times the rolling mill may be operational, but no steel has reached proper rolling temperature. This production delay, called a cold-steel delay, is indicative of the pits being outpaced by the rolling mill.

(4 to 6) In the soaking-pit operation, the pit must accept and heat a charge of ingots, hold these ingots at the proper temperature until they are rolled, and remain idle until another charge occurs. The percentage of time that the pits are heating steel, "coasting" with hot steel, and idle awaiting a charge is descriptive of soaking-pit utilization.

(7) The fuel consumption of the soaking pits, measured in Btu's per ton of ingot processed, was a parameter of considerable interest.

(8) The average soaking-pit heating time is closely related to No. 6.

(9) The average waiting time before steel is charged into a soaking pit is another measure of overload being experienced by the soaking-pit area and its related equipment.

2. RELATING PERFORMANCE TO OPERATING CONDITIONS

Once the nine operating and nine performance parameters were defined, the next step would normally be to select a set of conditions, run the simulation, and "see what happens."

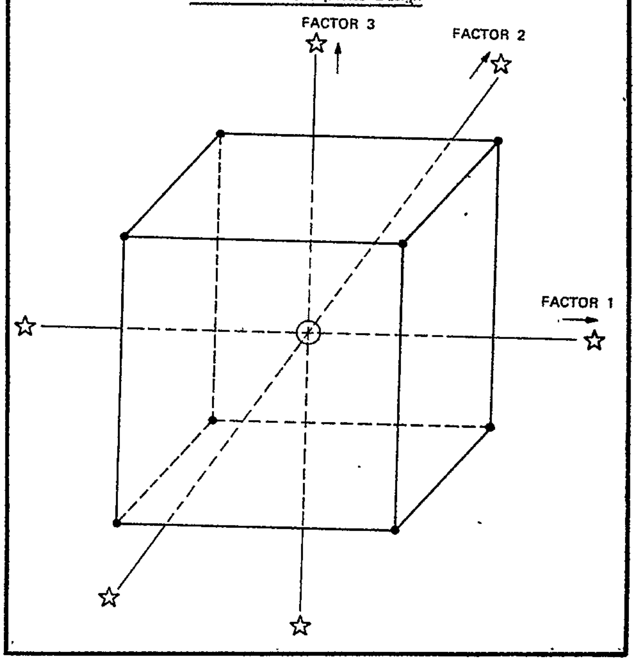
From building the simulation, it was obvious that an understanding of the interactive effects of the operating parameters was essential to achieve a successful solution to the problem. Only a systematic series of simulation runs would unravel these interactive effects. Because of the number of possible combinations of the operating parameters, it was not feasible to conduct a simulation run at every combination of parameters.

Consequently, a statistically designed experiment, in which the operating parameters would be used as the experimental factors and the performance parameters as the response variables, was the only feasible alternative.

A composite design[2] was selected. This type of design allows the investigation of linear and quadratic effects of the main factors and the linear interactive effects between the factors.

A composite design is based on a complete two level factorial design. The extremes of the regions of experimental interest serve as the two factorial levels of each factor. This basic design is augmented by conducting several center-point trials. These repeated trials, where each factor is set midway betweeen its factorial levels, are used to estimate the repeatability of the experiment. Finally, to allow estimates of quadratic main effects, star-point conditions are added to the factorial design. For these trials, all factors, except one, are fixed at their center levels. The remaining one is first fixed at a level less than the low factorial level and then at a level greater than the high factorial level. A composite design in three factors is shown schematically in Figure 2.

FIGURE 2
Three-Factor Composite Design



Designed Simulation Experiment (continued)

Table I shows the levels for the experimental program for studying the rolling-mill operation.

If only a selected portion of all the factorial combinations is examined, it is possible to reduce the required number of experimental trials. The degree of fractionating determines the highest order interaction (that is, two factor, three factor, and so forth) that can be studied. Interactions as complex as three factor are not often operative on a system. On the basis of this assumption, a quarter replicate of the factorial portion of the experiment was included in the final design. This permitted the estimation of all the two-factor interactive effects among the factors in the composite design.

A total of 90 experimental trials (64 factorial, 16 star points, and 10 center points) was used to estimate the effects of eight of the operating variables.

The remaining factor, the number of turns operated, was believed to be the single most important factor. In addition, its discrete nature did not readily lend itself to the composite design. Consequently, to estimate its effect, the entire 90-trial program was repeated (assuming 14, 17, and 20 scheduled operating turns). This permitted the estimation of the effect of turns scheduled and up to three-factor interactive effects involving the turns operated variable.

In general terms, the regression model assumed was

$$Y_k = \beta_o + \sum_{i=2}^{9} \beta_i X_i + \sum_{i=2}^{9} \beta_{ii} X_i^2 + \sum_{\substack{i,j=2 \\ i<j}}^{9} \beta_{ij} X_{ij} + \beta_1 X_1 + \beta_{11} X_1^2$$

$$+ \sum_{\substack{i,j=2 \\ i<j}}^{9} \beta_{1ij} X_1 X_i X_j + \varepsilon_K$$

where, Y_k is the performance variable

X_i $(i=1,2,\ldots,9)$ are the operating variables

ε_k is an error term assumed to be normally and independently distributed

Table 1

Levels of Operating Factors (Independent Variables) in Rolling-Mill Experiment

Factor	Design Level: Low Star	Low Factorial	Center	High Factorial	High Star
Unscheduled rolling delays, percent of time	0.0	5.0	12.5	20.0	30.8
Rolling rate, slab tons per operating minute	6.6	8.0	9.0	10.0	11.4
Number of soaking pits	-4	existing	+4	+8	+14
Unscheduled soaking-pit downtime, percent of time	0	5	10	15	22
Ingot tonnage delivered	-14,400	base	+10,000	+20,000	+34,400
Transit time relative to standard time, hour	-0.98	0.00	+0.75	+1.50	+2.68
Cold steel delivered, percent of total	0	0	10	20	34
Hot-top steel delivered, percent of total	8.4	30.0	45.0	60.0	81.6

For each of the 270 experimental trials, the parameters of the simulation model were equated to the appropriate experimental levels. The rolling-mill operation was simulated under these conditions for a four-week period, and the resulting performance statistics were noted.

For a complicated problem such as this, with the extremely large number of experimental combinations, this approach was the only feasible way to investigate the effect of the operating factors.

Even if the time constraint had not been prohibitive, the simulation model approach would have been a useful one. If this experimental program had been conducted over an extended period of time, extraneous factors would probably have changed and influenced experimental results. The simulation approach prevented this because these factors were fixed at selected levels.

Also, some experimental combinations of operating parameters would have been impractical from an operating point of view. Spending plant time to investigate these conditions would have been misuse of the facility and would have precluded conducting the complete experiment. These same combinations, however, were necessary from the mathematical point of view because the experimental design was balanced. Independent estimates of each effect were possible only with a balanced design.

After all runs were completed, the experimental results were analyzed by least-squares regression analysis. The backward elimination technique was used to select a regression equation describing the relationship between the parameters of mill performance and the nine operating factors. Only terms significant at the 5 percent level were retained in the model.

The resulting equations were too lengthy to warrant their inclusion in this paper. The number of significant terms ranged from 39 to 49.

A statistic that gives an indication of how well the models fit the data is the squared multiple correlation coefficient, R^2. This is the percentage of the total variability observed in the dependent variable, which was explained by the regression model. The R^2 statistics ranged from 94.2 percent to 98.8 percent for the nine models in this study.

Another statistic that gives an indication of the usefulness of a regression model is the standard error of estimate, SEE. The SEE is an estimate of the unexplained variation remaining after significant factors are considered. Comparing the SEE with the standard deviation of the center point trials gives an indication of the magnitude of the total unexplained variation relative to the inherent variation in the system. This comparison is shown in Table II.

3. PRESENTATION OF RESULTS

PLOTTING THE SIGNIFICANT EFFECTS

The estimated effects of each operating factor on each of the nine performance measures were calculated by using the regression models; they were then graphically presented to mill operating personnel. As an example, the effects of operating factors on tonnage produced are shown in Figures 3 through 10.

Table 2

Comparison of Standard Errors of Estimate With Standard Deviation of Center-Point Trials

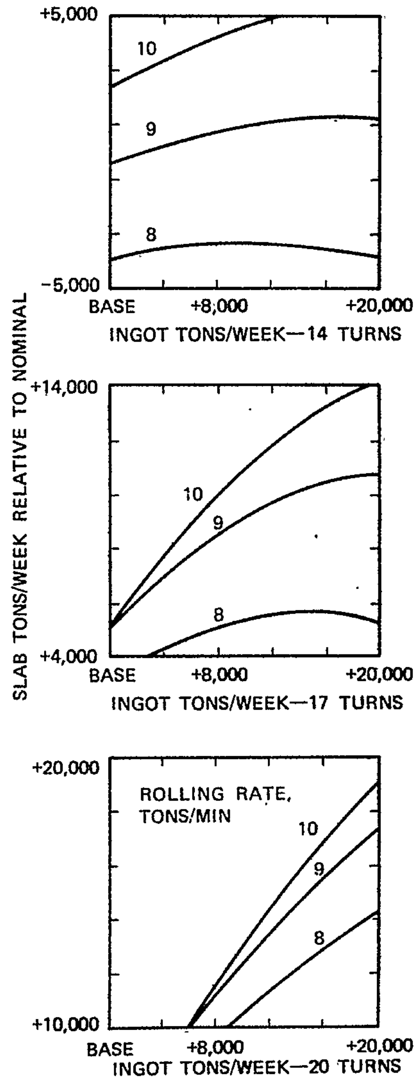
Performance Measure	Standard Error of Estimate	Standard Deviation
Slab tonnage produced	1024	669
Ingot tonnage diverted	1225	671
Cold steel delays, hr/turn	0.13	0.06
Pits heating, percent of time	1.5	1.0
Pits coasting, percent of time	1.6	1.0
Pits idle, percent of time	2.5	1.0
Fuel used, Btu/ingot ton	15	10
Average heating time, hr	0.25	0.21
Average waiting time, hr	0.20	0.15

Most of the effects depicted are interactions between two or three operating factors. A two-factor interaction means that the effect of one operating factor differs, depending on the level of the other operating factor. A three-factor interaction indicates that main effects are not independent of one another, nor are two-factor interactions independent of the missing main effect.

When generating the curves for any figure, the items specifically mentioned in the figure were set at levels within

FIGURE 3

Interactive Effect of Tonnage Delivered, Turns Scheduled, and Rolling Rate on Tonnage Produced



Designed Simulation Experiment (continued)

their experimental regions. Factors not specifically mentioned were set at their center experimental levels. (The number of soaking pits was set at the existing number.)

Figure 3 depicts a three-factor interaction between turns scheduled, tonnage delivered, and rolling rate. Production is almost directly related to rolling rate by using the 14-turn schedule. At any given rolling rate, production increases only slightly as tonnage delivered increases because the capability of the rolling mill is the limiting

FIGURE 4

Interactive Effect of Tonnage Delivered, Turns Scheduled, and Mill Delays on Tonnage Produced

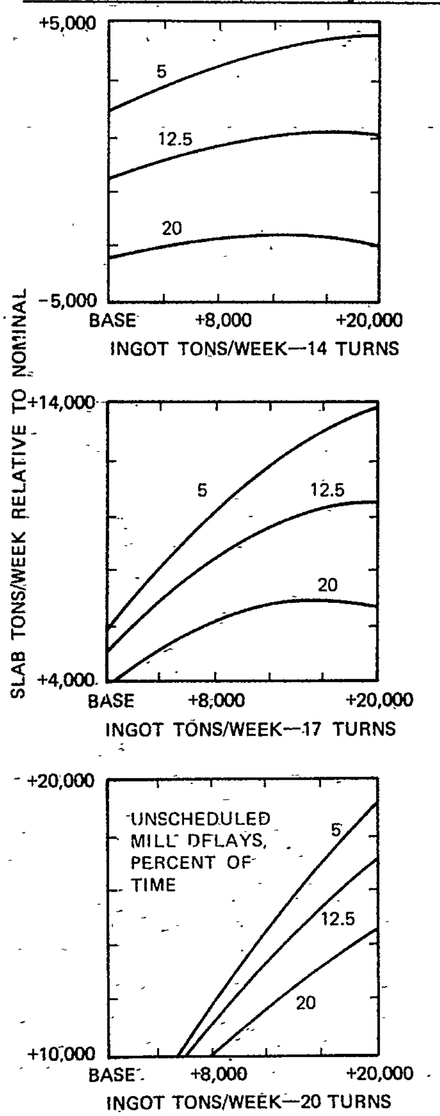
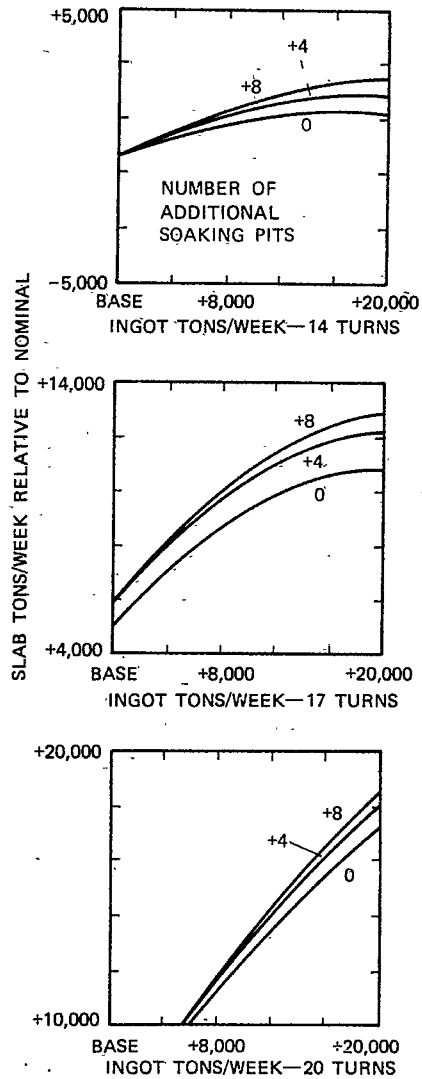


FIGURE 5

Interactive Effect of Tonnage Delivered, Turns Scheduled, and Number of Pits on Tonnage Produced



factor. At 17 turns, increases in the rolling rate at the higher delivery levels produce additional tonnage. At low delivery levels, increasing the rolling rate above 9 tons per minute has little or no effect because all or almost all of the delivered tonnage is being processed, even at the slower rate. The effect of rolling rate is less pronounced with the 20-turn operation because the greater availability of the rolling facility is the overriding factor.

A similar explanation can be advanced for Figure 4, which represents the interaction among turns scheduled, tonnage delivered, and unscheduled mill delays. Increased unscheduled delays has basically the same effect as decreasing the rolling rate.

The effect on production as a result of additional soaking-pit capacity is also dependent on the number of turns scheduled and the tonnage delivered. This interaction is portrayed in Figure 5. Four additional soaking pits lead to increased production with the 14-turn schedule only when the higher delivery levels occur. At the 17-turn schedule, the four additional pits increase production at any delivery level. The greater availability of the rolling mill at the 20-turn schedule reduces the effect of the additional soaking-pit capacity. In all three situations, the effect of eight additional pits is only beneficial to production at the high delivery levels.

FIGURE 6

Interactive Effect of Tonnage Delivered, Turns Scheduled, and Pit Availability on Tonnage Produced

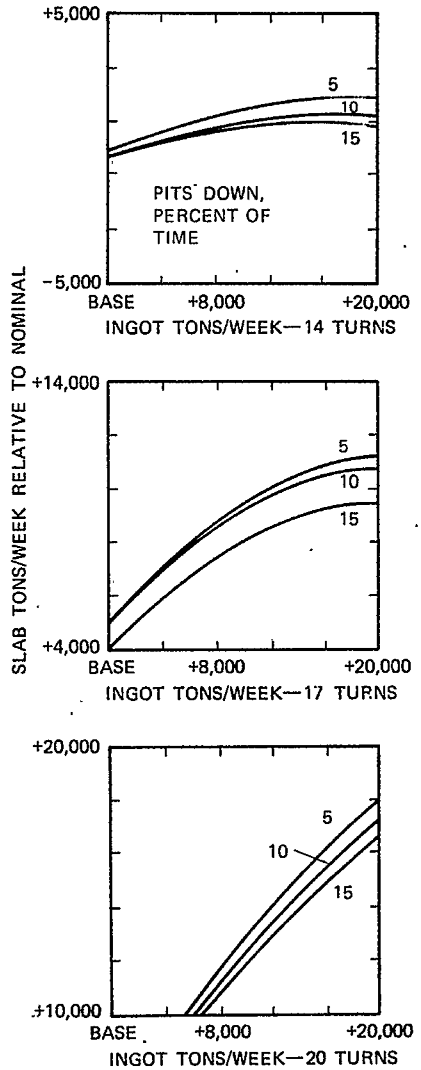
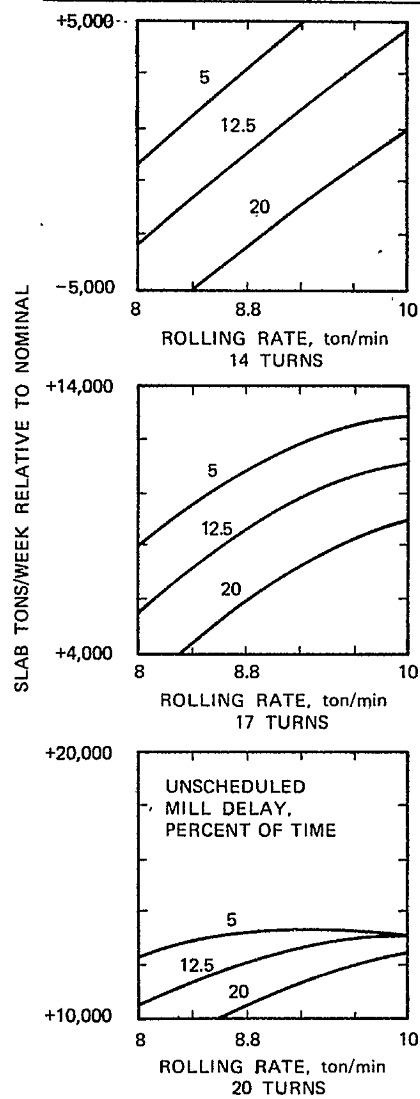


FIGURE 7

Interactive Effect of Turns Scheduled, Rolling Rate, and Mill Availability of Tonnage Produced



The amount of soaking-pit capacity is influenced by the number of pits and also by the amount of downtime on the existing pits—less downtime, in effect, being the same as having more pits. Because of this, an interaction similar to that shown in Figure 5 exists between turns scheduled, tonnage delivered, and soaking pit downtime. This effect is shown in Figure 6.

Figure 7 shows an interaction between turns scheduled, rolling rate, and unscheduled mill delays. The latter two are both measures of the rolling-mill capability. The interaction shows that increases in rolling-mill downtime can be compensated for by faster rolling rates, and vice versa. Since this figure assumes a fixed volume of delivery (nominal plus 10,000 tons) the importance of the interaction diminishes as more turns are scheduled. In fact, with the 20-turn schedule and considering the 80 percent yield, virtually all the delivered steel is processed, regardless of the rolling rate or mill availability.

FIGURE 8

Effect of Hot-Top Steel on Tonnage Produced

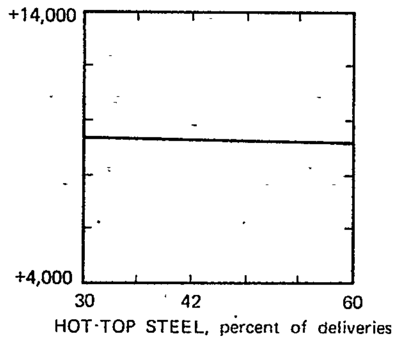


FIGURE 9

Effect of Cold Steel on Tonnage Produced

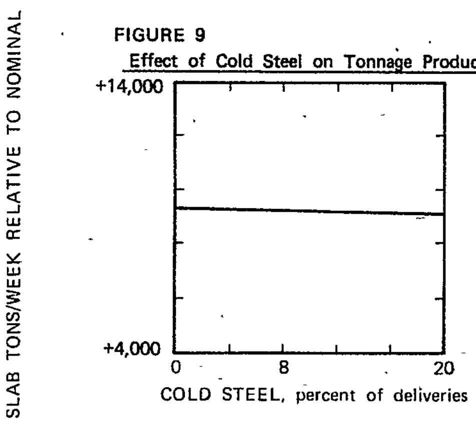
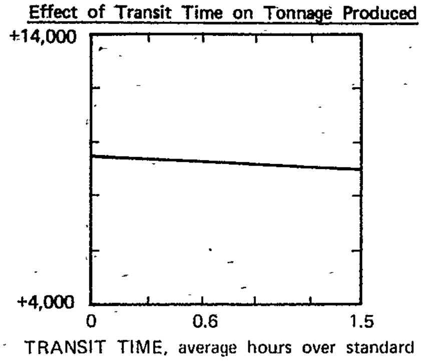


FIGURE 10

Effect of Transit Time on Tonnage Produced



Figures 8, 9, and 10 depict three factors that have linear effects, independent of any other operating factor, on the production. All three—proportion of hot-top steel, amount of cold steel, and longer transit times—increase demands on soaking-pit time, and consequently, decrease the throughput of the entire facility.

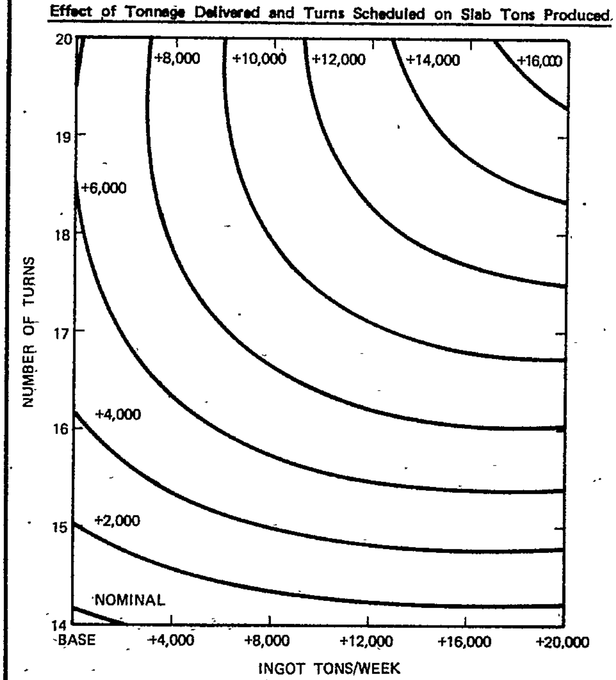
RESPONSE SURFACES

An alternative method of presenting the effects of the operating factors was through use of response surfaces.[2] A response surface is created by drawing lines representing equal response in the dependent, or performance, variable on a graph, the coordinates of which are two operating parameters.

Three response surfaces are shown in Figures 11 through 13. The two operating factors used as coordinates are tonnage delivered and turns scheduled. The response surfaces show the tonnage produced, tonnage diverted, and cold-steel delays predicted for any combination of the two operating factors used as

FIGURE 11

Effect of Tonnage Delivered and Turns Scheduled on Slab Tons Produced



coordinates. As before, the other factors were set at their center values when the predictions were made.

The response surfaces are read as if each were a topographical map. All tonnage figures are stated in relative

FIGURE 12

Effect of Tonnage Delivered and Turns Scheduled on Ingot Tons Diverted

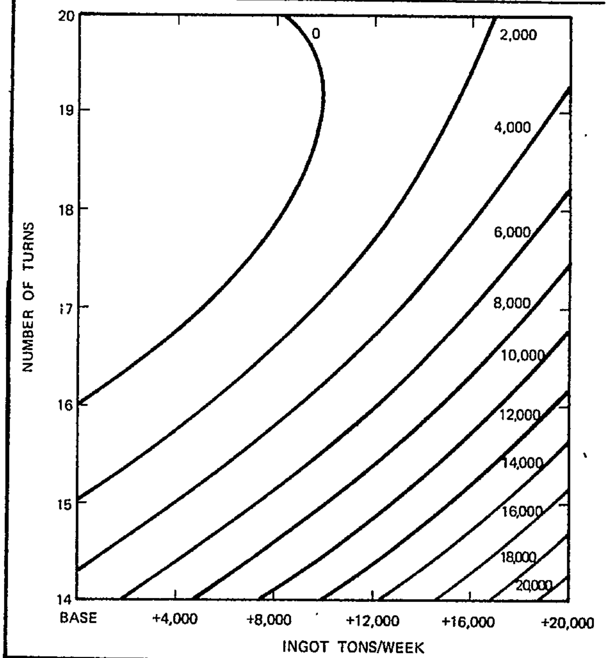


FIGURE 13

Effect of Tonnage Delivered and Turns Scheduled on Average Hours of Steel Delays

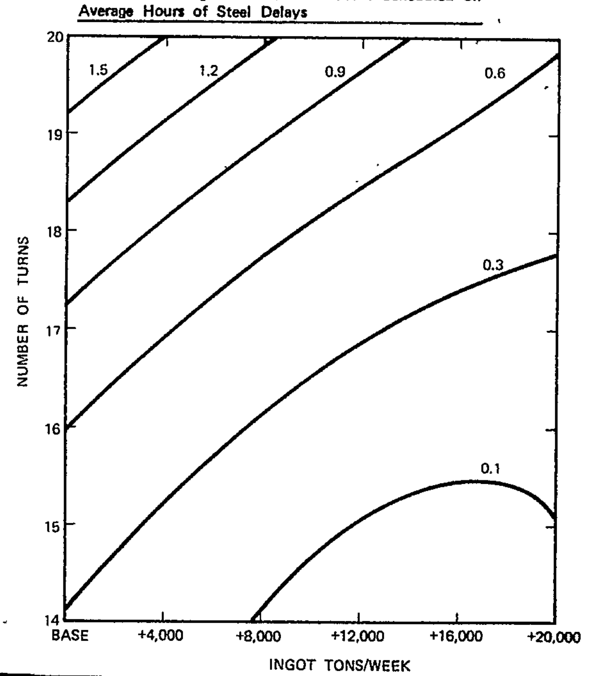
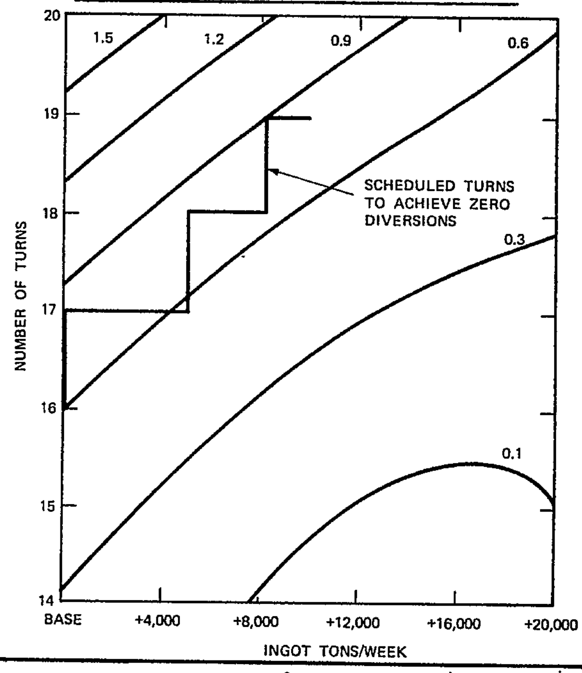


FIGURE 14

Average Hours of Steel Delays Resulting From Scheduling to Achieve No Steel Diversion



terms. The nominal production is that slab tonnage produced in 14 turns from the base delivered tonnage (Figure 11), diverted tonnage in this situation would be about 5000 tons (Figure 12), and cold-steel delays would be about 0.3 hour per turn (Figure 13).

Predicted changes in the response, or performance, variable as a result of a change in either operating factor used as a coordinate can be noted from the response surface. For example, an increase to 15 scheduled turns with the same tonnage delivered and an assumed 80 percent yield would result in additional production of 2500 tons (Figure 11). This is accomplished by a 3000-ton reduction in diverted deliveries (Figure 12).

4. AN APPLICATION

When considered as a group, the response surfaces can be used to aid in making operating decisions.

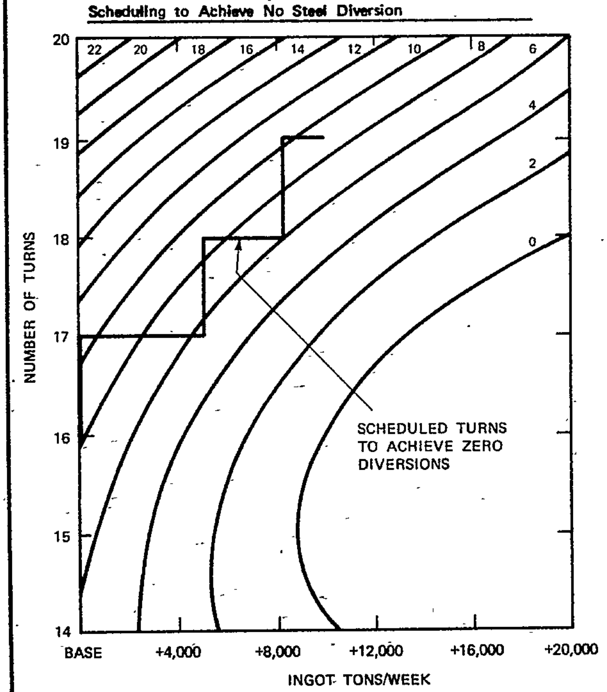
For example, a facility might elect to follow the strategy of not diverting any steel to inventory. It is assumed that all other factors are fixed at previously mentioned levels, the zero divert line on Figure 12 indicates that 16 scheduled turns would be required for the nominal delivery, 17 turns for up to 5,000 tons in excess of nominal, 18 turns for between 5,000 and 8,000 tons in excess of nominal, and 19 turns for between 8,000 and 10,000 tons in excess of nominal.

A line representing this relationship has been superimposed on the cold-steel delay and the soaking-pit idle response surfaces, Figures 14 and 15, respectively. These indicate that the "zero diversions" strategy can be expected to result in steel delays of between 0.6 and 0.9 hour per turn and between 6 and 10 percent idle soaking-pit time.

Using the response surface in this manner gives a quantitative basis for scheduling an appropriate number of turns. In addition, knowledge of the probable extent of rolling-mill idle time perhaps could allow the scheduling of small maintenance tasks during the scheduled rolling period. Likewise, with an estimate of idle soaking-pit capacity, management may elect to take some pits out of service for maintenance or fuel-conservation reasons.

FIGURE 15

Percent of Total Time That Pits Are Idle Resulting From Scheduling to Achieve No Steel Diversion



5. SUMMARY

As in the example presented, management decisions should utilize quantitative information. To do this, the process must be defined in mathematical terms. Simulation is one useful means of modeling any process. However, when the process is complicated and operating factors do not independently influence the operation, a simulation alone is not sufficient to completely understand the effect of each factor. Using a designed experiment in conjunction with the simulation is one way of doing this.

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