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Hot Strip Mill Transportation in Rourkela Steel Plant

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Abstract - This paper discussed possible adaptation of electronic transport means in Hot Strip Mill for improving finished product quality. The present system operating in Rourkela steel plant is discussed. Additional electronic means are proposed.

Keywords-Hot Strip Mill, Soft Computing, space mapping, surrogate model

I. INTRODUCTION

In the open market our steel industries are constantly facing challenges by new competitive materials, imports, rising labour costs and new complex technologies. The customers demands include tighter tolerance on thickness on steel strip, sheet and plate products. Being, perhaps, the oldest industry of the current civilization, cheap solutions for such challenges in steel industry are almost exhausted. It requires well planned, soundly conceived innovative technical changes.

Figure 1. Over view of hot strip mill..

For example let us consider the hot strip mill. When the slab is transported through the mill, the width, thickness, temperature or the incoming metallurgy can all be varied.

During the transport, there are internal disturbances or noise like mill thermal variation, electric subsystems functioning and improper operator adjustments.

Strip thickness can change due to change in rolling pressure, which among other factors may be affected by change in change in strip tension. This also can affect the flatness and width profile of the strip. Such problems are being tackled using opportunities offered by feedback control and systems engineering. Recently Rourkela Steel Plant (RSP) has adopted automation procedures and has implanted sensors for entry guide gap measurement in hot strip mill [1].

II. RSP HOT STRIP MILL

The annual capacity of the Hot Strip Mill of RSP is 15, 00, 000 tons of rolling slab. There are two walking beam type furnaces each of 225 ton/hour capacity. Out of the three roughing stands, the first one (R0/V0) is a combination of vertical stand and horizontal stand. The remaining two (R1 & R2) are 4 high horizontal stands. The R2 stand is followed by a delay table, a coil box and a crop shear respectively in the mentioned order.

It also contains 6 numbers (F1 to F6) of 4 high finishing stands and 2 hydraulic down coilers. Besides there are entry side guides prior to coil box, crop shear and F1 to F6. The entry guide gap is adjusted by a 10 kW AC motor using a 6.3:1 gear, rack and pinion arrangement. The products produced by SAIL Rourkela is having a specific weight of 15kg/mm and Total weight 17T. The width /gauge ratio is given in the following figure.

Figure 2. Range of products.(size wise)

III. TECHNICAL CHALLENGES IN HOT STRIP MILL

The automation cost of the hot strip mill is a fraction of the cost of loss that can occur due to customer dissatisfaction resulting in rejection of the finished product. Therefore, expenses on automation are not vital. What matters is the correct technical approach. In fact, it is the most vital factor in determining success or failure of the automation process.

Primarily, there are two technical approaches prevailing in the world.

1) For large complex systems like fully integrated steel plant, the hierarchy multilevel approach is weighed against the centralized I-level approach. Studies have shown that the former is preferred over the later in the steel industry fraternity.

2) Multilevel system design compared to controlled experimentation and regression analysis. In this case also the former is the winner as there is no reported success for approaches based on the later.

The hot mill processes are complex in nature due to complicated non-linear relationships. Therefore, mathematical models are almost non-existent either in closed or in open form.

IV. E-TRANSPORTATION IN HOT MILL AUTOMATION

The transportation of slabs from the beam type furnace to the coiler plays most important role in shaping the end product. This process needs engineering ingenuity for developing and designing working systems of reliability and performance capabilities. We shall discuss some of the identified components/subsystems like automatic gauge

control, System Structuring, increasing production capabilities etc. To address such issues, we will first look at the functional operation needed for the hot strip mill.

Functional Operation:

The automatic mill-set up is one of the most important functions of the hot strip mill. There shall be two primary inputs to the system. The first is the input slab data consisting of steel type, dimensions and temperature. The second is the finished product data which constitutes strip width, thickness, finishing temperature and coiling temperature. Besides them there is the knowledge data containing information on characteristics of mill, drive, steel as well as a mathematical model of the process (if possible at all) which is usually static. The relationship between the first two sets of data is highly nonlinear in nature and dependent on the third set. The automated system shall take the input information with the desired output information and use the knowledge information for proper set-up of the mill.

For example, suppose strip thickness, finishing temperature and division of load on the rolling stands are specified. Then, the system shall check to determine the available speed cone, roll bit or limitations on reduction, restriction on the strip shape and all other available criteria for setting up the mill to meet the required specifications. It will send reference signals to each stand speed regulator, each screw down position regulator for setting up the mill at the best delivery speed.

Additionally, the system can also provide settings for various types of products so that subsystems, like thickness gauge, width gauge & many other sideguides are automatically set up.

The system shall continuously receive feedbacks for on-line updating the model during the production of each coil. The system shall also keep abreast thermal changes of the mill, wearing of roll and performances of other subsystems.

When the metal enters the finishing stands, it is necessary to perform Vernier set-up calculations for all downstream stands. Its necessity arises due to the fact that the temperature measurement errors and hardness variation within given steel grades and between bars have negligible effect on delivery thickness and delivery temperature.

The transportation in hot strip mill area extends from the input side of the reheat furnace, through the furnace, roughing mills, finishing mills to the exit side of coilers. For such a transport system, the following five basic functions are required to be incorporated.

I. Slab thickness - On the continuous strip mill how many slabs are possible in the process.

II. Pacing of the mill - It shall control the processing rate of the slabs through the mill.

III. Temperature control - It is necessary to fix the finishing and coiling temperatures to the desired values.

IV. Estimation and setting up of the complete mill.

V. Process data logging - It can be useful in production control, quality control, engineering and management.

All computers deployed in the automation process are to be networked and the operators should be conversant with the controlling programs. For example, to avoid damage to cold rolls, the operator himself should be capable of reducing load on that stand and then gradually increase it as the rolls warm up. During this period the system redistributes the required load over the other stands.

Under difficult situations or contradictory logics, the system should be capable of warning the operator that such a situation is predicted and it will not be possible to execute it. Many a times the operator may not have time to switch to an alternative. However, if provided with earlier, the system can switch to such alternatives. For example, suppose a bar has been delayed between roughing and finishing stands due to some reason and has become too cold. Then it cannot be rolled to meet the required specifications. In such a situation the system can select a standard stock product and accordingly change the mill set-up. Then things can get going again.

Automatic Gauge Control:

The present steel market is extremely choosy about the strip flatness & way edges, gauge uniformity and width. Therefore, automation of gauge control is of prime importance in hot strip mill. The automation has to take into account both electrical and mechanical mill structure, products and their order of rolling out. Then the system can be given set up instructions for automatic gauge

control subsystem. Also the system can monitor the process based on these instructions.

The feedback principle can be applied for predicting the performance of the implemented automatic gauge control. Closed form mathematical equations shall be complicated since relationships between the strip and mill stands are highly non-linear. Therefore, we propose the use of artificial neural networks. As is established, artificial neural networks are suitable tools for efficient function approximation for any degree of nonlinearity between the input and output. Also, the adapting capability of the synaptic weights in artificial neural network is excellent. Therefore, if in future there is a demand for tighter tolerance on gauge, the gauge control subsystems gain can be increased accordingly, by retraining the artificial neural network. Usually, it will require additional inputs as well as a change in system configuration for the subsystems stability. Normally, use of conventional models shall involve high expenses on these heads. However, using artificial neural network model will require one time increase in training time of the network to take into account the additional inputs and outputs (if any).

System Structuring:

The structuring of the hot strip mill must aim at good performance, high reliability and lower cost. These are to be optimized by proper balance between hardware and software. Conventional engineering optimization based on calculus or mathematical search models will not be very suitable due to the complexities involved. The search space for optimization becomes complicated leading to difficulties in searching. Therefore, stochastic optimization schemes like particle swarm optimization (PSO) [2] or its variants shall be preferred in this scenario.

The transportation from the furnace to different locations in the plant is one of the involved processes in the steel plant. It is difficult to track the slabs, their deliveries to different points and returning back of trolleys to the original point of loading after delivering the products to desired destination, using manual or semi-automatic means. For complete automation, wireless sensor networks and RFID tags can be deployed for tracking the delivery of the materials in the transportation system. This system can be integrated using the stochastic optimization described above as an integral part of the subsystem.

Increasing production capabilities:

Adoption of automation can obsolete existing, tested and trusted facilities in existence. However, for increasing production, these are a necessity. For example for higher production, mills shall require high capacity motors. Usually, these will be of much larger size. While, the motor size will increase on one hand, on the other the distance between the stands is to be kept constant. Thus it will put a space constraint, because the motor is to be installed in the same amount of space as that for the low productivity motor. Again the more the production is, the more is the thermal and mechanical wear of the motor. This will reduce the life of the motor. Therefore, design of motors becomes an optimization problem, which considers the size of the available space for installation, production capability of the motor and its life time. Of course, such technologies have been developed for implementation in today's motor design.

Again, the plant has to decide on the top delivery speed and fix a limit on it. It is because it is impracticable to keep the head end on the runout table or constantly thread the coilers at high speeds. Usually, the front end is associated with aerodynamic lift characteristic. So, it will take to air and result in disastrous effect. For practicability, the mill should accelerate automatically after the entry of the head end into the coiler. In fact, the automation shall monitor gauge, mill temperatures, motor loads and thereby keep an overall optimal set up for the mill so that there will be no cobbling or neck-downing in width of the produced strip

V. SOFT COMPUTING FOR TRANSPORTATION MANAGEMENT

In the above sections, it has been indicated that the Hot Strip Mill is a complex system involving high degree of non-linearity to be effectively modelled using mathematical tools. Also, it has been pointed out that artificial neural network is capable of modelling nonlinear relations efficiently. Similarly, it has been said that proper management of the transportation shall need optimization and particle swarm optimization has been proposed as a stochastic means. These two soft-computing techniques are briefly discussed in the following.

Particle Swarm Optimization (PSO):

It is a powerful and effective optimization method, similar in some ways to Genetic Algorithms (GA) and other evolutionary algorithms. It requires less computing, storage and

(generally) lines of code. The basic algorithm is simple to understand and implement.

Suppose an optimization problem needs the optimization of a given fitness function of M variables. Then the problem space is M -dimensional (one dimension per variable). In this problem space, a collection or swarm of particles is defined, where each particle is assigned a random position corresponding to a candidate solution of the optimization problem. Each of these particle positions is evaluated for a scalar cost depending on how well it solves the problem. These particles then soar in the problem space subject to both deterministic and stochastic update rules to new positions, which are subsequently evaluated.

As the particles move around in the problem hyperspace, each particle remembers its own personal best position that it has ever found, called its local best and the best position found by any particle in the swarm, called the global best. On successive iterations, particles are "tugged" toward these prior best solutions.

Overshoot and undershoot combined with stochastic adjustment explore regions throughout the problem hyperspace, eventually settling down near a good solution.

This process can be visualized as a swarm of bees in a field [3]. Their goal is to find the location with the highest density of flowers. Without any knowledge of the field *a priori*, the bees begin in random locations with random velocities looking for flowers. Each bee can remember the locations where it found the most flowers, and somehow knows the locations where the other bees found an abundance of flowers. Torn between returning to the location where it had personally found the most flowers, or exploring the location reported by others to have the most flowers, the ambivalent bee accelerates in both directions altering its trajectory to fly somewhere between the two points. Along the way, a bee might find a place with a higher concentration of flowers than it had found previously. It would then be drawn to this new location as well as the location of the most flowers found by the whole swarm. Occasionally, one bee may fly over a place with more flowers than had been encountered by any bee in the swarm. The whole swarm would then be drawn toward that location in addition to their own personal discovery. In this way, the bees explore the field.

Constantly, they are checking the territory they fly over against previously encountered locations of highest concentration hoping to find the absolute highest concentration of flowers. Eventually, the bees' flight leads them to the one place in the field with the highest concentration of flowers. Soon, all the bees swarm around this point.

Unable to find any points of higher flower concentration, they are continually drawn back to the highest flower concentration.

The following steps are accomplished on each particle individually:

1. Initialize a population of particles with random positions and velocities in M dimensions in the problem space.
2. For each particle, evaluate the desired optimization fitness function in M variables.
3. Update the particle velocity. The velocity of the particle is changed according to the relative locations of p_{best} and q_{best} . It is accelerated in the directions of these locations of greatest fitness according to the following equation [3]:

$$v_n = w * v_n + c_1 \text{rand}() * (g_{best,n} - x_n) + c_2 \text{rand}() * (p_{best,n} - x_n) \quad (1)$$

Here, v_n is the velocity of the particle in the n -th dimension and x_n is the particle coordinate in the n -th dimension, c_1 and c_2 are scaling factors that determine the relative "pull" of p_{best} and q_{best} (previous work has shown that a value of 2.0 is a good choice for both parameters [3]), and $\text{rand}()$ is a random number uniformly distributed in interval (0,1). The parameter w is a number, called the "inertial weight", in the range [0,1], which specifies the weight by which the particle's current velocity depends on its previous velocity and how far the particle is from its personal best and global best positions. Numerical experiments have shown that the PSO algorithm converges faster if w is linearly damped with iterations starting at 0.9 and decreasing linearly to 0.4 at the last iteration.

4. Move the particle. Once the velocity has been determined, it is simple to move the particle to its next location. The new coordinate is computed for each of the dimensions according the following equation $x_n = x_n + v_n$

5. Loop to step (2) until a criterion is met, usually a sufficiently good fitness or a maximum number of iterations

Artificial Neural Network (ANN):

The ANN can be classified as supervised and unsupervised networks. In the present application the use of the network is for function approximation. Therefore, supervised ANN is discussed here. In this category, the Feed Forward neural networks are the most popular and most widely used models in many practical applications. They are known by many different names, such as "multi-layer perceptrons."

Figure 3 illustrates a one-hidden-layer FF network with inputs $x_1, \dots, x_n$ and output $\hat{y}$. Each arrow in the figure symbolizes a parameter in the network. The network is divided into *layers*. The input layer consists of just the inputs to the network. It is followed by a *hidden layer*, which consists of any number of *neurons*, or *hidden units* placed in parallel. Each neuron performs a weighted summation of the inputs, which then passes a nonlinear *activation function* σ , also called the *neuron function*.

Figure 3. A feedforward network with one hidden layer and one output.

Mathematically the functionality of a hidden neuron is described by

$$\sigma \left(\sum_{j=1}^n w_j x_j + b_j \right) \quad (1)$$

Where the weights $\{w_j, b_j\}$ are symbolized with the arrows feeding into the neuron.

The network output is formed by another weighted summation of the outputs of the neurons in the hidden layer. This summation on the output is called the *output layer*. In Fig. 3 there is only one output in the output layer since it is a single-output problem. Generally, the number of output neurons equals the number of outputs of the approximation problem.

The neurons in the hidden layer of the network in Fig. 3 are similar in structure to those of the

perceptron, with the exception that their activation functions can be any differential function. The output of this network is given by

$$\hat{y}(\Theta) = g(\Theta, x) = \sum_{i=1}^{nh} w_i^2 \sigma \left(\sum_{j=1}^n w_{i,j}^1 x_j + b_{i,j}^1 \right) + b^2 \quad (2)$$

Where n is the number of inputs and nh is the number of neurons in the hidden layer. The variables $\{w_{i,j}^1, b_{j,i}^1, w_i^2, b^2\}$ are the parameters of the network model that are represented collectively by the parameter vector Θ .

Note that the size of the input and output layers are defined by the number of inputs and outputs of the network and, therefore, only the number of hidden neurons has to be decided when the network is defined. The network in Fig. 3 is also referred to as a three-layer network, counting input, hidden, and output layers.

In training the network, its parameters are adjusted incrementally until the training data satisfy the desired mapping as well as possible; that is, until $\hat{y}(\Theta)$ matches the desired output y as closely as possible up to a maximum number of iterations.

The nonlinear activation function in the neuron is usually chosen to be a smooth step function. The default is the standard sigmoid

$$\text{Sigmoid}[x] = \frac{1}{1 + e^{-x}} \quad (3)$$

that looks like fig. 3 bellow.

Figure 4. Sigmoid Activation Function.

ANNs with more than one hidden layer are known as multilayered neural network. In Fig. 5 a multi-output FF network with two hidden layers is shown.

Figure 5. A multi-output feedforward network with two hidden layers.

The number of layers and the number of hidden neurons in each hidden layer are user design parameters. The general rule is to choose these design parameters so that the best possible model with as few parameters as possible is obtained. This is, of course, not a very useful rule, and in practice one has to experiment with different designs and compare the results, to find the most suitable neural network model for the problem at hand.

For many practical applications, one or two hidden layers will suffice. The recommendation is to start with a linear model; that is, neural networks with no hidden layers, and then go over to networks with one hidden layer but with no more than five to ten neurons. As a last step one may try two hidden layers.

The output neurons in the FF networks in are generally linear; that is, they do not have any nonlinear activation function after the weighted sum. This is normally the best choice if one has a general function, a time series or a dynamical system to be modelled. However, if one is using the FF network for classification, then it is generally advantageous to use nonlinear output neurons.

VI. CONCLUSION

In this paper, the automation process in Steel Plant is proposed to be modelled using soft-computing means. The difficulties in modelling of the transport system at the Hot Strip Mill due to involved non-linearity are discussed. At the end the soft-computing techniques are briefly outlined.

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