Materials Science and Technology

ISSN: 0267-0836 (Print) 1743-2847 (Online) Journal homepage: http://www.tandfonline.com/loi/ymst20

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To cite this article: A. Kermanpur, A. Ebnonnasir & M. Hedayati (2007) A novel analytical–artificial neural network model to improve efficiency of high pressure descaling nozzles in hot strip rolling of steels, Materials Science and Technology, 23:8, 951-957, DOI: 10.1179/174328407X213099

To link to this article: https://doi.org/10.1179/174328407X213099

Published online: 19 Jul 2013.

A novel analytical–artificial neural network model to improve efficiency of high pressure descaling nozzles in hot strip rolling of steels

A. Kermanpur*, A. Ebnonnasir and M. Hedayati

Hot strip mills use hydraulic descaling to remove oxide scales from steel strip formed after the reheat furnace and during hot rolling. In the present work, a novel analytical–artificial neural network (AANN) model was developed to improve the efficiency of high pressure (HP) hydraulic descaling operation using flat spray nozzles. The AANN model is able to analytically compute the spray force and depth and to estimate the spray impact using an artificial neural network approach. The combined model was trained based on the industrial data from the hot strip rolling mills of Mobarakeh Steel Complex. The spray angle, spray pressure, vertical spray height and water flowrate were all considered as the main input parameters of the HP descaling operation. The AANN model can predict the spray force, impact and depth under any given descaling condition. A sensitivity analysis was carried out using the combined model. It is shown that, among all process parameters, the spray angle followed by the spray height are the most important parameters affecting the spray impact. The model developed can be used as a proper tool to improve the efficiency of the descaling system in terms of achieving the highest spray impact under any process condition.

Keywords: High pressure hydraulic descaling, Hot strip steel rolling, Neural network modelling, Analytical modelling

Introduction

High pressure (HP) hydraulic descaling operation is widely used to remove the scales formed on the surface of hot strip steels after preheating furnace and during hot rolling. These scales, so called rolled in defects, affect significantly the surface quality of the hot rolled products and reduce the life time of work rolls. Generally, the following types of scale formation are distinguished:[1]

(i) primary scale, formed during reheating in the rolling mill furnace

(ii) secondary scale, formed after descaling by the edging pass and during and after the roughing operation

(iii) tertiary scale, formed during final rolling before and in between the stands of the finishing mill.

According to the detailed analysis by Blazevic,[2] rolled in scale on products of a hot strip mill can lead to ~30 related surface defects.

Different methods are usually used to control the rolled in scale formation, including low temperature of the strip at the entry, descaling, intersand cooling, skin cooling, roll cooling and lubrication. Among them, the descaling operation is one of the most frequently used methods to remove primary and secondary scales from strip steels. Traditionally, HP flat spray nozzles are used in this application in slab, billet or bloom operations. The force of the spray impinges the steel surface breaking up the scale and moving it away. Optimising header design can help improve product quality and reduce energy costs for the mill.

To improve productivity and quality, steel industries are adopting process modelling techniques to reduce defects, scrap, design lead time and cost.[3] Many process models have so far been presented for water spray cooling of hot rolled steel bars.[4,5] Nevertheless, less systematic work has been published on modelling of HP hydraulic descaling using flat spray nozzles. Previous studies have been performed to determine the mechanisms of scale removal.[6–9] An analytical model was proposed by Wada *et al.* correlating the impact pressure of the hydraulic descaling with the water consumption at a pressure of 9·8 MPa, water pressure, rolling speed and distance between the material and the nozzle based on the measurements using both a plasticine and pressure converter.[10] Recently, a computer model was introduced to study the stresses that develop within the oxide formed on the surface of reheated steel slabs.[11] A criterion based on the velocity and amount of water as well as the force of the impact was proposed to determine the feasibility for oxide removal using HP descaling nozzles. Some steel industries have also

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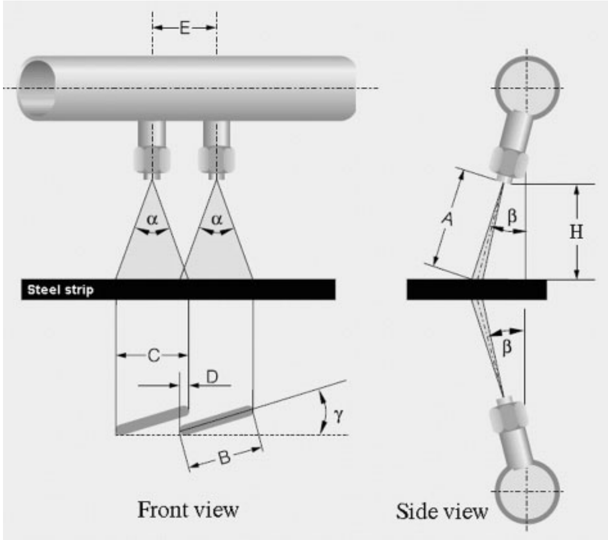
Published by Maney on behalf of the Institute
Received 22 March 2007; accepted 10 May 2007
DOI 10.1179/174328407X213099



1 Schematic of positioning of HP descaling spray nozzles

developed private simulation programmes for their own spray nozzles.[12,13] Owing to the complexity of the turbulent, two phase spray formed during the operation, available numerical models cannot be used to study the fluid mechanics of the system. According to the authors' knowledge, no artificial intelligence model has so far been presented for HP descaling.

In the present work, a combined analytical–artificial neural network (AANN) model is presented to investigate the process parameters of HP flat spray nozzles for descaling of hot strip steels. The process parameters considered include spray pressure and flowrate, spray angle and vertical spray height. The ability of the model to predict spray impact, force and depth is discussed and the main controlling parameters of the descaling operation are evaluated.

Model theory

Descaler parameters

Hydraulic descaling nozzles are normally flat (jet) spray nozzles. Figure 1 shows the schematic of positioning of spray nozzles.[14] The exact definitions of the spray characteristics such as spray angle, width, depth (thickness) and impact distribution and the specification of the operation parameters such as spray pressure, flowrate and vertical height are the first two steps to be taken when a spray nozzle is being designed.

Since the water droplets are immediately acted upon by external forces (e.g. gravity and moving gases), the spray angle is measured close to the nozzle orifice. This phenomenon is called spray *convergence*. Four spray angles describing the width of the spray are very common: 22, 26, 30 and 40° nozzle tips, each available at different flow sizes. To achieve design flexibility, the spray width is identical for all nozzle tip sizes at identical pressures and spray heights.[14]

After a particular nozzle type (size and spray angle) has been selected, the force depends only on the water pressure and the water flow. If the water pressure is fixed and limited as in many existing installations, the only variable to play with is the area of impact. Spray angle and spray thickness (depth) are the two nozzle design parameters affecting the area of impact. It is also a fact that with increasing inclination angle, both the spray width and the spray thickness grow. Hence the area of impact increases, consequently lowering the impact.

The vertical spray height also plays an important role as it has a direct effect on the spray width, and hence on the area of impact. Significant improvements could be achieved in both product quality and cost savings in existing rolling mills by reducing the spray height.

In the following sections, the analytical and artificial neural network models developed to estimate the spray force, impact and width will be presented.

Spray force

No nozzle can exceed the theoretical total force. This force is the same for all nozzles of the same flowrate and pressure

$$F_t = \rho Q V \tag{1}$$

where F_t is the total impact force (N), ρ is the density (kg m^{-3}), Q is the flowrate (m^3 s^{-1}) and V is the velocity (m s^{-1}). All the above variables affect the flowrate and velocity of the spray, which in turn affect impact. The impact is the most important parameter of spray descaling. The spray impact is controlled by mass per unit time, spray angle, concentration of the spray, operating pressure, drop size and air friction. Mass per unit time is the product of the density and flowrate. Velocity is affected by drop size in that smaller drops lose velocity faster due to air friction. Larger drops will maintain velocity further from the orifice.

The final force equation for a water spray can be reduced to[15]

$$F_t = 0{\cdot}235 Q P^{1/2} \tag{2}$$

where Q is the the flowrate (L min^{-1}) and P is the pressure (bar). The theoretical total force that the nozzle can produce is a valuable number. Nevertheless, to compare this number to the actual measured values of the spray force, more mathematics needs to be applied.

Spray impact

Why neural network?

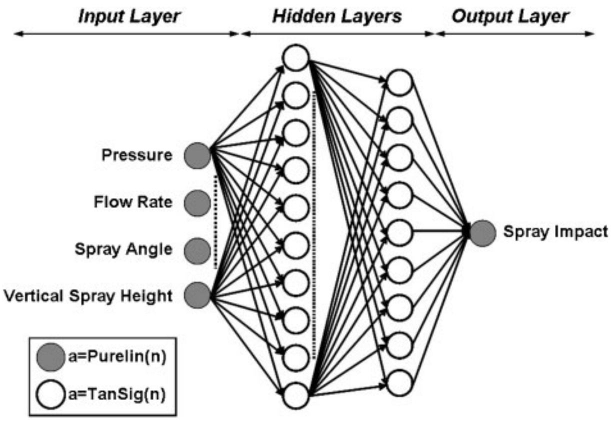
The theoretical maximum impact is the theoretical force that the nozzle will produce along the centerline of the spray pattern provided there are no losses in the nozzle. A specific spray impact can be defined as impact per unit impingement area of the entire spray pattern

$$I_m = \frac{F_t}{BT} \tag{3}$$

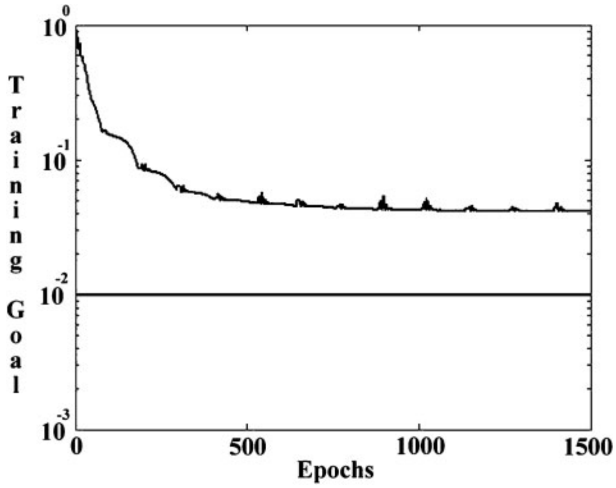
where I_m is the specific impact (N mm^{-2}), B is the spray width (m) and T is the spray depth or thickness (m) (*see* Fig. 1). Spray angle and spray concentration are important variables in determining specific impact. Smaller spray angles will have a smaller impingement area with more drops per unit area. The smaller the impingement area of the spray, the higher the specific impact is of the spray pattern produced. Impingement area A_I can be calculated via the following equation

$$A_I = 2H \tan\left(\frac{\alpha}{2}\right) 2H \tan\left(\frac{\theta}{2}\right) \tag{4}$$

where H is the spray height (vertical distance from the nozzle tip to measuring area on the strip surface, *see*



2 Schematic of neural network model (connectors of all neurons are not shown for simplicity)



3 Training curve of neural network model

Fig. 1) (m), α is the spray angle and θ is the lateral spray angle. Trigonometry can estimate the impingement area but as the spray height increases, the error percentage of equation (4) increases. The lateral spray angle θ and the (transverse) spray angle α are only accurate close to the orifice.

The spray impact depends on the spray width and depth.[14] The impact increases when spray width or depth decrease. The impact also increases when pressure or flowrate increases. But the increasing pressure also influences the spray width and depth that influences the impact again. It can be seen that the process parameters are highly dependent on each other. Another complication is the spray convergence. Depending on pressure and capacity, the spray tends to start to pull in as it leaves the orifice. Therefore, it is not possible to analytically compute the real impingement area. Therefore, individual functions have to be developed for every nozzle type and process conditions.

Owing to the complications described above, an artificial neural network (ANN) approach was used to estimate the spray impact under any given condition. The ANN is a very powerful tool to model the relationship between the input and output parameters of complicated systems such as hydraulic descaling. This approach is a non-linear statistical analysis technique, especially suitable for simulation of systems which are hard to be described by physical models.[16] It provides a way of linking input data to output data using a set of non-linear functions. The network architecture and the training procedure are discussed in the following sections.

Network architecture

In the present work, a standard feed forward network with two hidden layers was designed by a trial and error procedure. The number of neurons in the input and output layers are determined by the number of input and output variables respectively. To find an optimal architecture, different numbers of neuron in the hidden layer were considered and root mean square (RMS) error for each network was calculated. Figure 2 shows the schematic representation of the neural network architecture employed in the present study. The input layer included four variables: spray pressure, water flowrate, spray angle and vertical spray height. The inclination and offset angles were assumed to be constant, which are 10 and 15° respectively. The output variable of the model was the spray impact.

Training process

The ANN models are often trained by the *backpropagation* method.[17] The term backpropagation refers to the manner in which the gradient is computed for non-linear multilayer networks. The early standard algorithm consisted of assigning a random initial set of weights to the neural network, then presenting the data inputs, one set at a time and adjusting the weights with the aim of reducing the corresponding output error. This was repeated for each set of data and then the complete cycle was repeated until an acceptably low value of the sum of squares error was achieved. Such an algorithm is usually both inefficient and unreliable, requiring much iteration to converge if it converges at all. Therefore a number of variations of the standard algorithm (based on other optimisation techniques) have been developed. One of the most useful and fastest algorithms is Levenberg–Marquardt.[17] A potential difficulty with the use of such algorithm is over fitting. In this situation, the network is said to be memorising data patterns rather than predicting them. One way to reduce this problem is employing Bayesian regularisation.

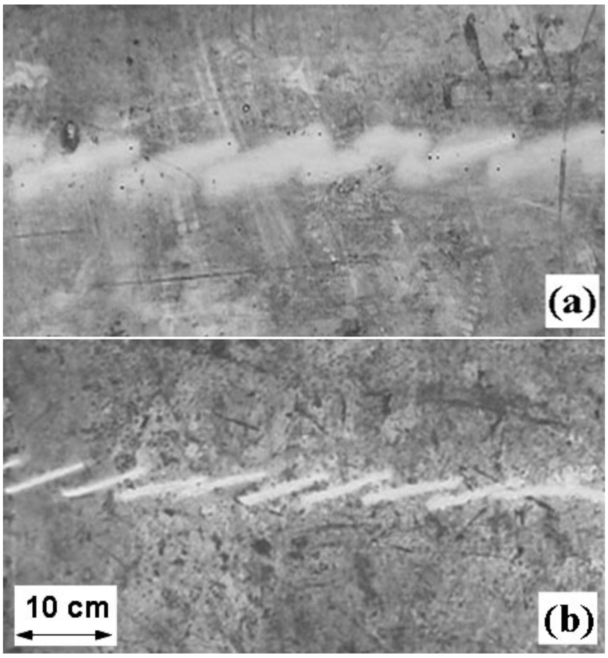
In the present study, Bayesian regularisation was used to improve the ability of the network for predicting more precise results from unseen input patterns. All available data from the hot strip mills of Mobarakeh Steel Complex (MSC) were divided into two parts: 33 sets for training procedure and ten sets for test.[18] To improve the network performance, inputs and outputs were normalised in the range from −1 to 1. Figure 3 shows the training curve of the ANN model. It can be seen that the performance is ~0·041 for the goal 0·01. Several intentional disturbances have been also applied after ~500 epochs, but the same performance was again achieved.

Spray depth

Spray depth (thickness) of a descaling nozzle depends on spray pressure, flowrate, vertical height, inclination angle and spray angle. Experimental investigations showed the following expression[12]

$$t=\frac{F_{\mathrm{tot}}\times N}{2I(H+25)\tan(\alpha/2)\times 0{\cdot}6127} \tag{5}$$

where t is the spray depth, F_{tot} is the total spray force, I



a low spray impact; *b* high spray impact

4 Real pictures of aluminium sheet surface operated under two different spray descaling conditions

is the spray impact, H is the vertical spray height, α is a calculated spray angle (depending on the spray pressure and flowrate) and N is a constant depending on the nominal spray angle and inclination angle. To find out the values of α and N, the following procedure was introduced.

According to the previous studies on the HP spray nozzles, one can have[12]

$$F_t = \frac{2Q}{1000\cdot 6}\left(2P\times 10^8\times\rho\right)^{1/2}\frac{\sin(\alpha/2)}{\alpha} \tag{6}$$

By inserting equation (2) into equation (6), one can have

$$k = \frac{\sin(\alpha/2)}{\alpha} = \frac{F_t}{\frac{2Q}{1000\cdot 6}\left(2P\times 10^8\right)^{1/2}} \tag{7}$$

and therefore

$$f(\alpha) = \sin(\alpha/2) - k\alpha \tag{8}$$

where k is a constant. Equation (8) has many answers. It was found that the first non-zero, positive value for α represents a better match to experiments. Using the Newton–Raphson method, one can have

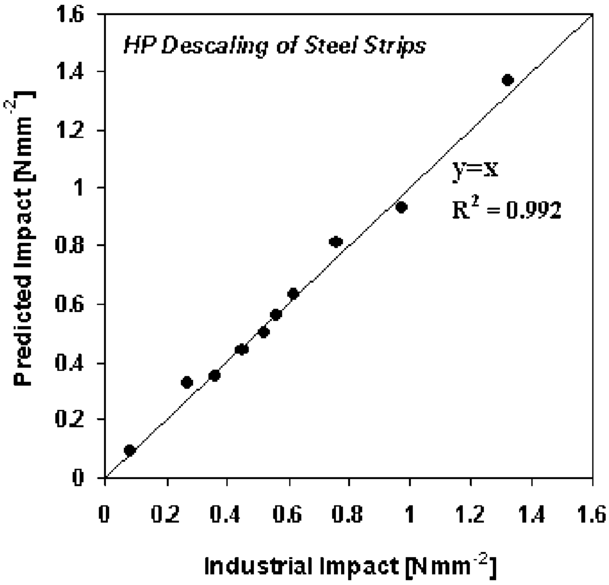
$$\alpha_{n+1} = \alpha_n - \frac{\sin(\alpha_n/2) - k\alpha_n}{0\cdot 5\cos(\alpha_n/2) - k} \tag{9}$$

Taking the initial values of n=0 and α_0=2π, the value of α can be obtained after several iterations. It should be noted that the α value depends on k and in other words, P and Q.

Results and discussion

Importance of spray impact

Figure 4 shows the pictures of an aluminium sheet surface operated under two different spray descaling conditions: low spray impact (bad design) and high spray impact (improved design). These results were achieved under the pressure of 180 bar and the same spray height, but different nozzle designs.[18] Frankly, the higher and more concentrated the spray impact, the better descaling operation (Fig. 4*b* versus *a*). The objective is then to specify the process conditions for achieving a maximum amount of spray impact for any given spray configuration. In this regard, the relationship between different parameters should be taken into account.



5 Comparison between predicted and industrial values of spray impact for unseen (test) datasets

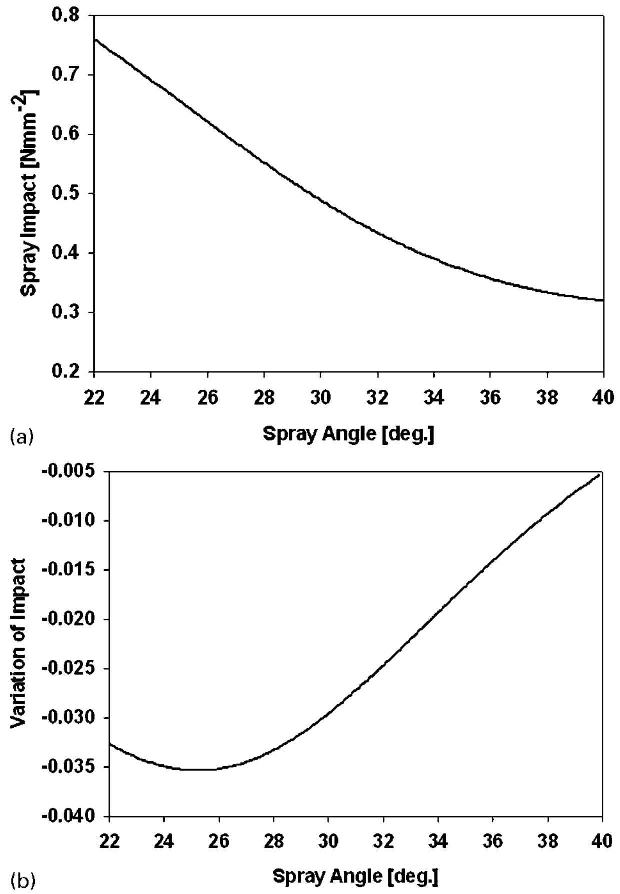
Model validation

The performance of the ANN model was evaluated against ten unseen (test) industrial dataset (out of 43 total datasets, i.e. ~23%) under different nozzle designs and process conditions. Figure 5 compares the predicted spray impact by the present ANN model with the industrial one for all unseen datasets. Although the use of Bayesian regularisation may result in a higher performance error for the training datasets, the error for the test datasets is reduced which is an indication of higher ability of the network to predict more precise results from unseen patterns. A good agreement can be seen in Fig. 5 with the correlation coefficient R^2 of ~0·992, showing the ability of the ANN model to predict the accurate results.

Parameter sensitivity

The validated AANN model was used to study the contributions of different parameters to the spray impact and hence the efficiency of the descaling operation. To perform such sensitivity analysis, the nominal working range for the considered input parameters was specified as shown in Table 1. Each individual input parameter was changed with the increment of 0·1 at the mean values of all other parameters. The spray impact versus each individual parameter was then evaluated.

Figure 6*a* shows the effect of spray angle on the spray impact in the entire range of 22–40°. It can be seen that increasing the spray angle decreases the spray impact. The slope of this curve at each value, or the first derivative, is an indication of the impact sensitivity to the spray angle. Figure 6*b* shows the variation of impact



6 Effect of spray angle on *a* spray impact and *b* variation of impact

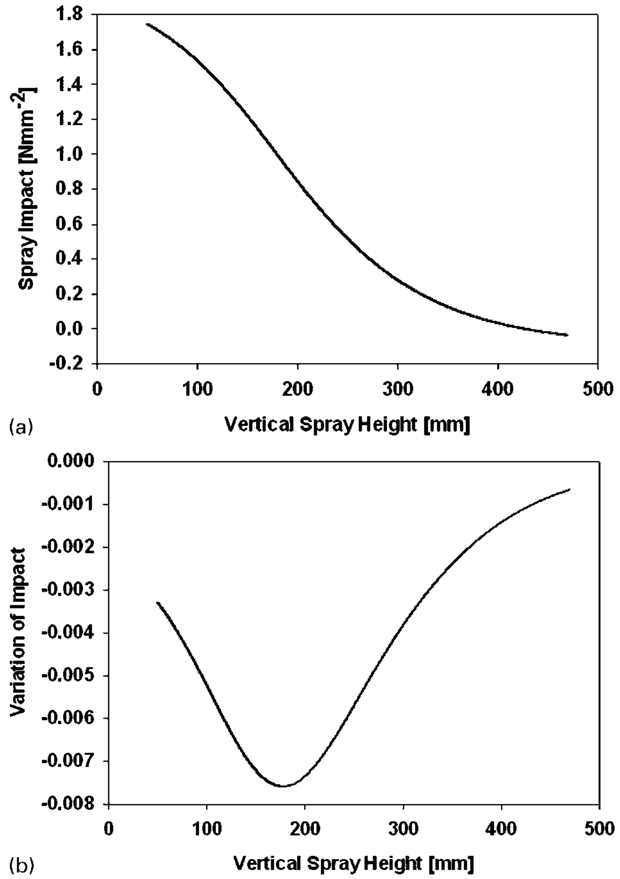
for different spray angles. It is shown that the effect of spray angle on the impact is higher for the lower values.

Figure 7*a* and *b* shows the effect of vertical spray height on the spray impact and variation of impact respectively in the entire range of 50–470 mm. It is shown that increasing the vertical spray height rapidly decreases the spray impact, and a maximum occurs at $\sim$180 mm. Therefore, below or above this value, the variation of impact due to changing vertical spray height is decreased.

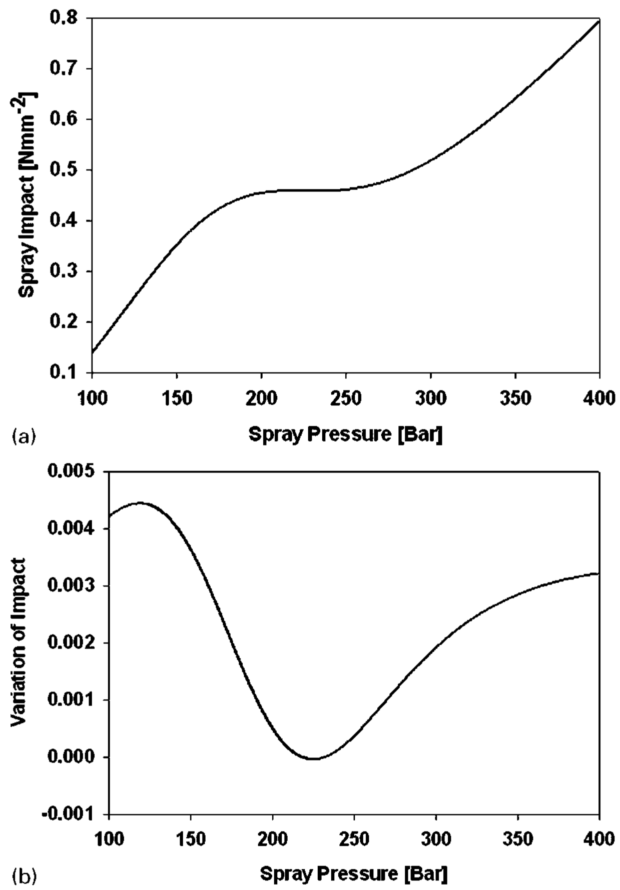
Figure 8*a* and *b* shows the effect of spray pressure on the spray impact and variation of impact respectively in the entire range of 100–400 bar. It can be seen that increasing the spray pressure has a direct influence on the spray impact, and there is a minimum at $\sim$230 bar. In other words, the effect of spray pressure on impact is more significant for the low and high pressure values. As described above, the increasing pressure also influences the spray width and depth which influence the impact again. This clearly shows that the process parameters are highly dependent on each other.

Table 1 Nominal range of different input parameters of ANN model

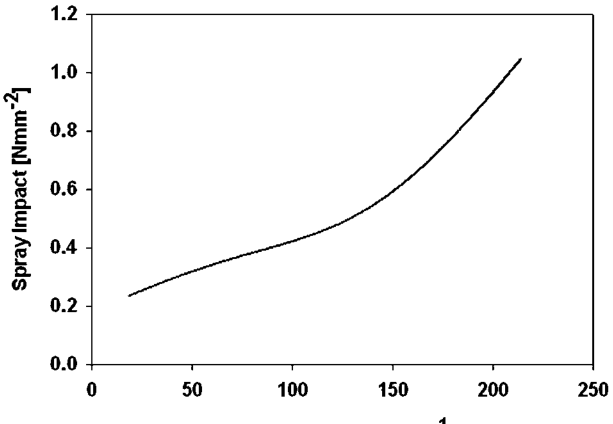
	Value	
Parameter	Min.	Max.
Spray angle, °	22	40
Spray pressure, bar	100	400
Water flowrate, L min^{-1}	18	214
Vertical spray height, mm	50	470



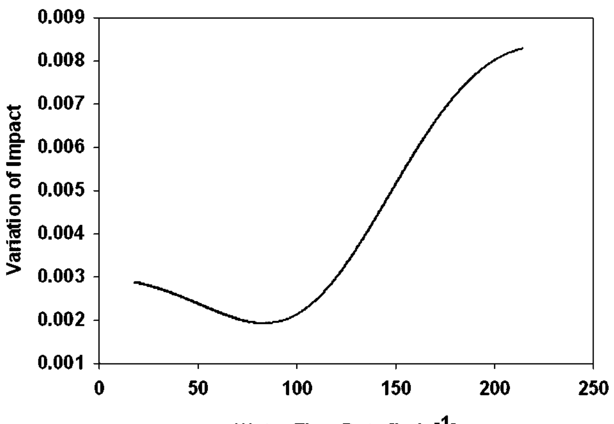
7 Effect of vertical spray height on *a* spray impact and *b* variation of impact



8 Effect of spray pressure on *a* spray impact and *b* variation of impact

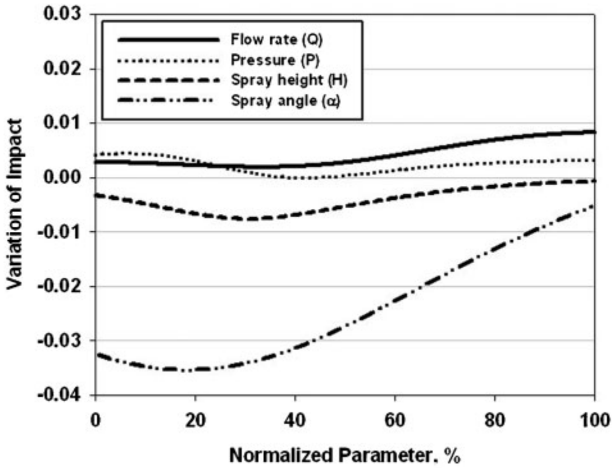


(a)



(b)

9 Effect of water flowrate on *a* spray impact and *b* variation of impact



10 Comparison of contributions of input parameters to variation of spray impact under normalised condition

Figure 9*a* and *b* shows the effect of water flowrate on the spray impact and variation of impact respectively in the entire range of 18–214 L min^{-1}. It is shown that increasing the water flowrate has a direct influence on the spray impact, and this effect is more significant for the lower values of flowrate.

The contributions of different input parameters to the spray impact are compared in Fig. 10 using the normalised values of all parameters in their entire nominal range. Interestingly, it is shown that the influence of these parameters on the spray impact decreases in the following order: spray angle, vertical spray height, water flowrate and spray pressure. Therefore, it can be concluded that a descaling nozzle with a lower spray angle positioned in as small as possible vertical spray height would increase the spray impact, consequently the efficiency of the descaling operation. However, it should be noted that the spray overlap (*D* in Fig. 1) is also a very important parameter in descaling operations. Changing any parameter that affects the impingement area could also alter the spray overlap. An optimum value of overlap is usually needed; the *D* value should be high enough in order not to remain any scale on the strip surface, and also should not be decided very high due to its inverse effect on the spray impact.[14] The present AANN model is in progress to also consider the effect of all input parameters on the spray overlap.

Conclusions

A combined AANN model was developed to evaluate the efficiency of a high pressure hydraulic descaling operation of hot strip steel rolling. The efficiency improvement was based on achieving a maximum amount of spray impact. The spray force and depth (thickness) were analytically predicted, while a neural network model within a Bayesian framework was used to predict the spray impact. The model was validated against several experimental data from an industrial hot strip mill. It was found that among all the process parameters of spray angle, vertical spray height, spray pressure and water flowrate, the most important one is the spray angle, the lower values of which result in a higher impact. The vertical spray height is also an important parameter affecting the impact. It was also shown that the effect of each individual parameter on the spray impact is not the same in the whole range of variation.

Acknowledgements

The authors would like to acknowledge the financial support of Mobarakeh Steel Complex of Iran according to the contract no. 48114345–166. They also appreciate the assistance of Mr A. Keyyeganeh and Dr M. R. Toroghinezhaad for their comments.

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