Design of deep learning on intelligent levelling system for industry 4.0 technology

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Abstract. Sheet metal is widely used in the industry for metal forming purposes, such as metal stamping and laser cutting as shown. It is often winded and stored in a coil form in order for better transportation. In the recent years, industry 4.0 has been a widely discussed topic in terms of industry manufacturing solutions, the manufacturing is required to be more flexible, efficient and also require more customization. In conventional coil levelling system, the machine settings are often tuned by the experienced technicians with many years of experiences. However, as industry 4.0 focused on information process through real objects, it is required to digitize the experience through deep learning method. Therefore, it is required to be adapted through data information transfer between real world and machines, or even machines to machines. In addition, the data information is often processed and analysed through computers which are often desired to mimic the operations of the experienced machine technicians through machine learning or deep learning methods. This paper is aimed to describe and develop the deep learning algorithm with application based on coil levelling system. Finally, through this paper, design of the deep learning algorithm with application based on coil levelling system is verified.

1 Introduction

The metal forming industry is considered as a main part in the mass production of automotive, electronics and communication or even coils service centres. The conventional metal forming production line can be seen in Fig. 1, where it consists of a coil line and a press machine as the two main components of the production line. The coil lines provide the overall handling of the production such as levelling the coil sheet and sheet transportation to the press machine. The press machine provides the forming process of the production.

The schematics of the coil levelling machine can be illustrated in Fig. 2. The main components of a conventional coil line are the decoiler and the levelling machine consists of several rollers. The coil is stored on the decoiler, which is used to unwind coils of sheet metals and pass it through leveller to level the sheet metal using rollers. In addition, it also feed to the press machine for metal forming process. Once the material is threaded inside

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the leveller, the material is then going through alternating bending of stretching and compression levelling process by rollers, from which process the ultimate goal is to remove shape defects and to flatten sheet metals for other applications [1].

Once the material is levelled, it is then transported to the press machine for metal forming process. The levelling part of the process is considered as the most important part of the coil handling system as many of the blanking processes require the sheet to be flat for the press to form the important shapes. In addition, the coil service centres require the sheet to be flat to stack up the sheets for packing purpose.

In the past few years, smart manufacturing or industry 4.0 has been a widely discussed topic in many different manufacturing industries across the world. Smart manufacturing is focused on cyber physical system (CPS) [2], with the operations of the physical world through information processing via information networks such as IoT. Therefore, intelligent manufacturing is required to be adapted through data information transfer between real world and machines, or even machines to machines. In addition, the information is often analysed through computers which are often desired to mimic the operations of the experienced machine technicians. Through machine learnings or deep learning methods to catch up the intelligence from experienced technician can certainly fill the existing gap and needs in levelling process to reach the goal of the industry 4.0.

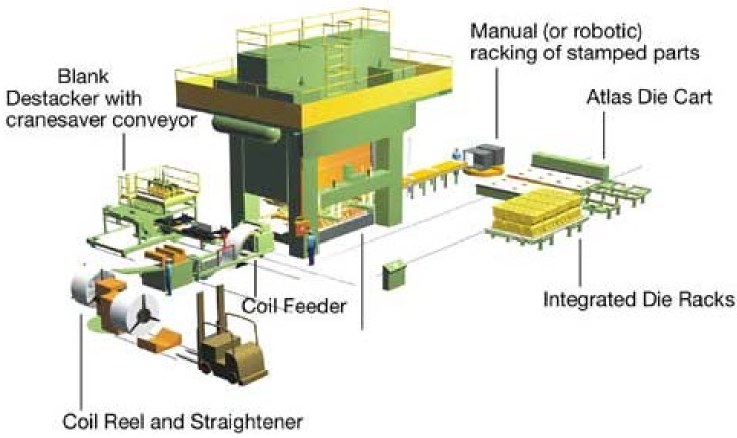

Fig. 1. Conventional metal forming production line [3].

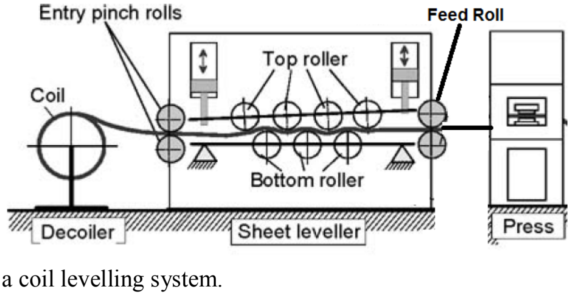

Fig. 2. Schematics of a coil levelling system.

2 Background theory

1.2 Roller levelling

The principle of roller levelling is the use of non-flat metal materials undergoing series of elastic bendings by rollers. The elastic bending process consistes of alternating positive and negative bending stresses of the metal material to overcom the material's pre-existing residual stress that caused the material's original non-flatness. Through series of such bending process, the goal is to reduce or even remove the material's residual stress so as to traighten and flatten the metal material. This process can be considered and modelled as an elastic beam of plate going through series of elasitc bending. To simply the idea, an Euler-Bernulli beam as shown in Fig. 3 is adopted to describe the elastic behaviour of the sheet metal in the levelling process. When a sheet metal beam processes through roller levellers, as shwon in Fig. 3 and measured against its neural axis, each section of the sheet metal beam will have one portion with compressive load and the other holds extensive load. Accoring to Euler-Bernulli beam model [4], for a prismatic beam having thickiness h and width b, its maximum normal stress caused by bening moment M occurs at farest distance from its nueral axis.

$$\sigma_{max} = \frac{M}{I} \cdot \frac{h}{2} \tag{1}$$

where I is the second moment of area about neutral axis. The given moment is the result of its internal normal stress σ which can be described by:

$$M = \int_{-\frac{h}{2}}^{+\frac{h}{2}} \sigma by\, dy \tag{2}$$

Here y is the distance measure from the beam's neural axis. Assume the stress-strain relation is

$$\sigma = Ee + Fe^n \tag{3}$$

in which strain can be written as $e = y/R$, the intermal bening moment can then be written as:

$$M = \int_{-\frac{h}{2}}^{+\frac{h}{2}} \left(\frac{Eby^2}{R} + \frac{Fby^{n+1}}{R^n} \right) dy$$
$$= \frac{E}{R} I_1 + \frac{F}{R^n} I_n \tag{4}$$

where $I_1 = \int_{-\frac{h}{2}}^{+\frac{h}{2}} by^2$ and $I_n = \int_{-\frac{h}{2}}^{+\frac{h}{2}} by^{n+1} dy$

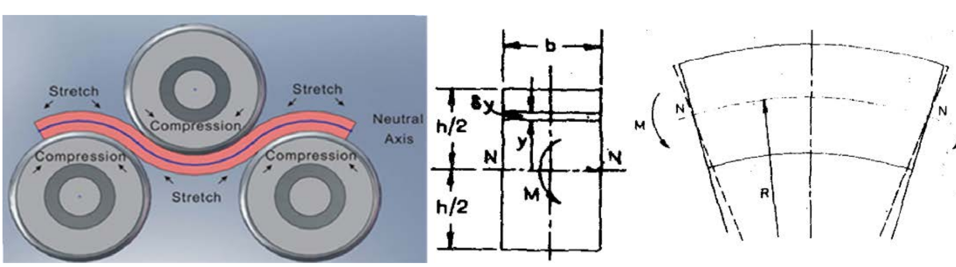

Fig. 3. Levelling theory schematics with bending.

2.2 Deep learning

There are three main categories of deep learning methods, such as convolutional neural networks (CNN), deep belief networks (DBN) and stacked auto-encoder (SAE) [5]- [8].

Since this application is more suitable to an unsupervised learning, a stacked auto-encoder neural network is applied. Stacked auto-encoder is a type of neural networks which contains multiple layers of sparse auto-encoders in which the output of each layer is connected to the inputs of the sequential layers [9]. The schematic plot of auto-encoder is shown in Fig. 4. The features of the stacked auto-encoder can be used in different dimension. In addition, one of the advantages of this algorithm is that it does not share the problem of gradient diffusion.

Supposed that there are only a set of unlabeled training examples that is $\{x(1),x(2),x(3),\ldots\}$ where xi ∈ Rn, and y is the predicting target value. An auto-encoder network is an unsupervised learning algorithm which applies backpropagation and setting the target values to be equal to the inputs. That is $y(i)=x(i)$.

An auto-encoder takes an input with transformation process from the input layer to the hidden layer. Such process is called encoding. On the other hand, the transformation process from the hidden layer to the output layer is called decoding. Therefore, the encoding and decoding process is presented by

Auto-encoder

$$d = S(W_1x+b_1) \quad (1)$$

$$y = S(W_2x+b2) \quad (2)$$

Where S represents sigmoid function, d represent the hidden layer and W_1 represents the weights matrix between input layer and hidden layer. On the other hand, W_2 represents the weights matrix between the hidden layer and the output layer and b_i represents the bias. As a result, the auto-encoder learns a function of $\hbar(w,\ b)\ (x)=x$. In addition, the auto-encoder is also trained with back-propagation algorithm used for optimization such as gradient decent. Supposes there is m number of training samples, the cost function for one sample is:

$$J(W,b;x,y)=\frac{1}{2}\left\|h_{w,b}(x)-y\right\|^2 \quad (3)$$

$$J(W,b)=\left[\frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\left\|h_{w,b}\left(x^{(i)}-y^{(i)}\right)\right\|^2\right)\right]$$

$$+\frac{\lambda}{2}\sum_{l=1}^{n_1-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_l-1}\left(W_{ji}{}^{(l)}\right)^2 \quad (4)$$

where λ represents the weight decay parameter, n1 represents the number of layers n the network, s1 represents the number of units of layer l, also called a weight decay term, which tends to decrease the magnitude of the weights and helps to prevent overfitting.

In addition, by adding sparsity constraints, it will help to find the useful features, which constrains the activation of hidden units to small value, and make the overall cost function to be

$$Jsparse(W,b)=J(W,b)+\beta\sum_{j=1}^{s}KL(\rho \parallel \hat{\rho}_j) \quad (5)$$

where

$$\mathrm{KL}(\rho \parallel \hat{\rho}_j)=\rho\log\frac{\rho}{\rho_j}+(1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_j} \quad (6)$$

where:

$KL(\rho \parallel \hat{\rho}_j)$	sparsity penalty term
β	controls the weight of the sparsity penalty term
$\hat{\rho}_j$	average activation of hidden unit j
ρ	sparsity parameter
s	number of hidden units

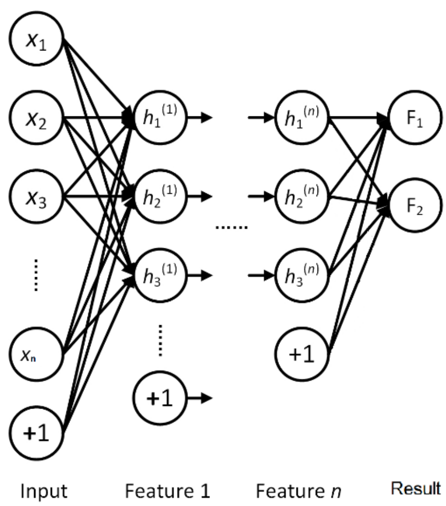

Fig. 4. Schematics of auto-encoders.

3 Methods

In this research, it is required to analyse the coil set residual stress as it is often found to be the most common defects amount coils. In addition, the amount of residual stress is different from the outer coil to the inner coil. In order to simulate such circumferences, the experiment is carried out by feeding different sheet metal material with different pre-rolled circumference to simulate the coilset residual stress from outer circumference of the coil to inner circumference of the coil. The sheet metal that is used in this experiment is the most commonly used SPCC cold rolled steel in the industry. Each coil has outer diameter and inner diameter, the inner diameter is set as 508 mm as it is an international standard for every coil. The common outer diameter is often set as 1200 mm. Therefore, to simulate such coil, set relationship, the 3 different circumferences have chosen to simulate the coils from 1200 mm outer diameter to 1000 mm and to 800 mm as shown in Fig. 5. This will identify the residual stress amount the coil. Two different thickness 0.6 and 0.8 mm, width and pre-rolled circumference have used as the input factors for this experiment. Each sheet metal is fed into the leveler; it is going through 9 rolls with alternate bend which breaks the residual stress caused by coil set and level the sheet metal material. After each of the sheet metal is leveled, it is moved to the measurement table as shown in Fig. 6. The flatness of each sheet metal sample is measured. The inlet and outlet roll indentation is adjusted to find the best position for fitting such curvatures.

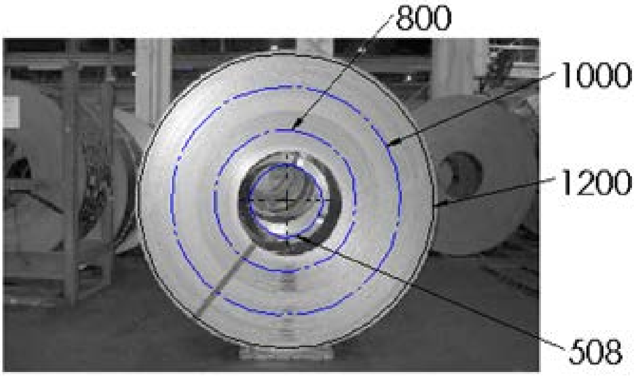

Fig. 5. Coil with different section of circumference.

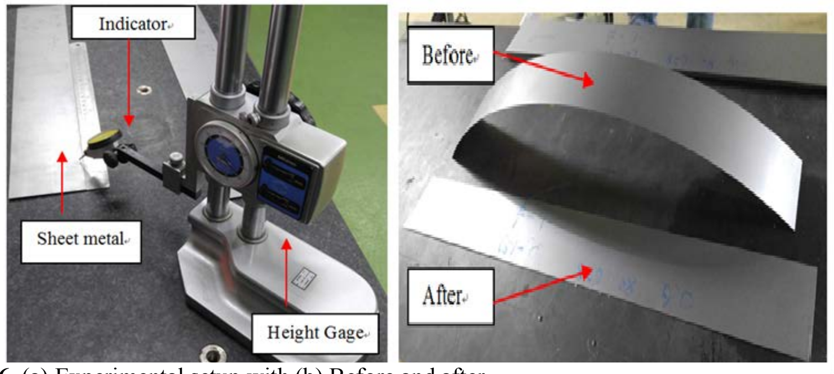

Fig. 6. (a) Experimental setup with (b) Before and after.

4 Results and Discussions

The data are simulated and examined between the simulated value and the real experimental value. The results are shown in both Fig.7 and Fig.8. The success rate of the algorithm increases as the number of sample increases. It is divided into 4 different circumference categories which represent the coil usage from outer diameter to inner diameter. It is shown that the algorithm does not function well within the previous 200 samples. However, this algorithm is reaching to steady state after 600 samples to achieve successful rate around 90%. In general, it is observed that the success rate of the simulation will be more if the parameters are chosen properly. It is concluded that SAE algorithm is shown to have effect on such application. In the future work, other deep learning methods can be used to compare such application and improve on current solutions.

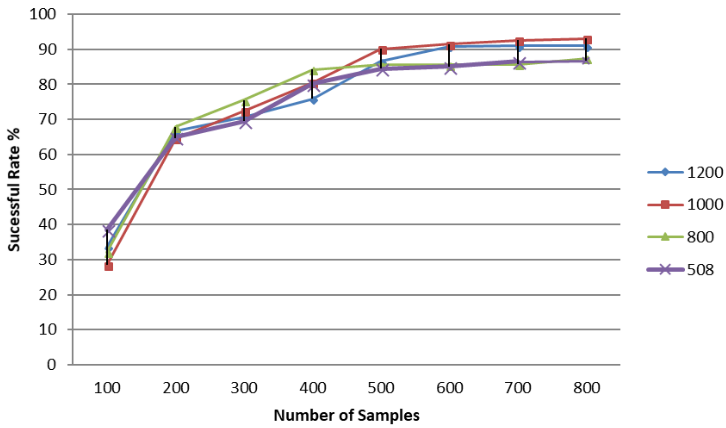

Fig. 7. Successful rate vs number of samples with 100s of samples at 0.6 mm.

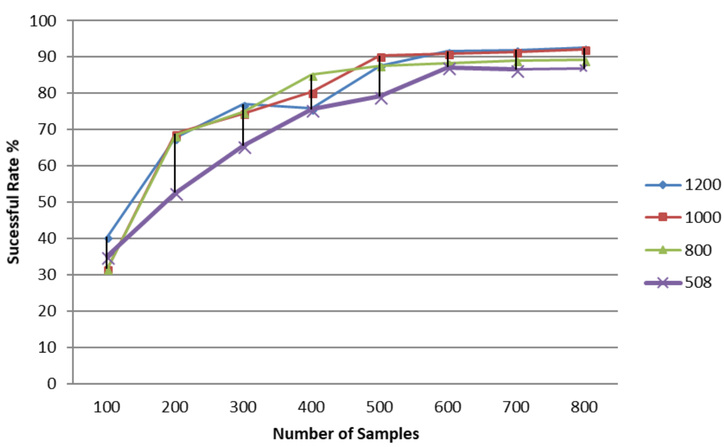

Fig. 8. Successful rate vs number of samples with 100s of samples at 0.8 mm.

5 Conclusions

The aim of this research is to design an intelligent levelling system for industry 4.0 technology. In this paper, conventional mechanics theory is discussed with supporting theory. In addition, deep learning theory is applied with supportive mechanics theory. The main achievement of this research is to digitalize the past experiences from a senior machine technician. In the research, the relationship between coil set residual stress and the roll indentation were conduction and compared with the operator experiences. Finally, the simulated data have shown to have over 90% of the success rate with sufficient number of samples.

References

1. P.B. Mellor, Engineering Plasticity, London: Van Nostrand Reinhold Company, (1973)
2. B. Sniderman, M. Mahto, and M. Cotteleer, Industry 4.0 and manufacturing ecosystems, Deloitte University Press, 2016. [Online]. Available: http://dupress.deloitte.com/dup-us-en/focus/industry-4-0/manufacturing-ecosystems-exploring-world-connected-enterprises. (Accessed 9 10 2016).
3. G.S. Vasilash, Pressworking: Cross-Bar Press Considerations, Automotive, 15 4 2000. [Online]. Available: http://www.adandp.media/articles/pressworking-cross-bar-press-considerations. [Accessed 20 5 2015].F. De Lillo, F. Cecconi, G. Lacorata, A. Vulpiani, EPL, **84** (2008)
4. T. Shogo, F. Yoneaki, Recent trend and problems of straightening technologies of thick plates, Journal of the Japan Society for Technology of Plasticity, pp. 408-11, (1999)
5. B. Wu, L. Chan, T. Lee, and L. Ao, A study on the precision modeling of the bars produced in two cross-rolls straightening, in J. Mater. Proc, Tech, (2000)
6. J. Xue, L. Cui, X. Hu, and X. Liu, Analysis of contact angle and curvature during roller levelling process, China Metal, vol. 19(2), pp. 23-6, (2009)
7. H. Huh, J. Heo, and H. Lee, Optimization of a roller levelling process for Al7001T9 pipes with finite element analysis and Taguchi model, Int. J. Mach. Tool. Manuf., vol. 43, pp. 345-50, (2003)
8. E. Doege, R. Menz, and S. Huinink, Analysis of the levelling process based upon an analytic forming model", CIRP Annals - Manufacturing Technology, p. 191–194, (2002)
9. E. Theis, Everything you need to know about flatteners and levelers for coil processing, THE FABRICATOR, 2 (2003)