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The sustainability of neural network applications within finite element analysis in sheet metal forming: A review

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ABSTRACT

The prediction of springback in sheet metal is vital to ensure economical metal forming. The latest nonlinear recovery in finite element analysis is used to achieve accurate results, but this method has become more complicated and requires complex computational programming to develop a constitutive model. Having the potential to assist the complexity, computational intelligence approach is often regarded as a statistical method that does not contribute to the development of a constitutive model. To provide a reference for researchers who are studying the potential application of computational intelligence in springback research, a review of studies into the development of sheet metal forming and the application of neural network to predict springback is presented in this research paper. It can be summarized as: (1) Springback is influenced by various factors that are involved in the sheet metal forming process. (2) The main complexity in FE analysis is the development of a constitutive model of a material that has the potential to be solved by using the computational intelligence approach. (3) The existing neural network approach for solving springback predictions is unable to represent all the factors that affect the results of the analysis.

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1. Introduction

Sheet metal forming has been extensively used in the automotive components manufacturing. One of the problems encountered in the sheet metal forming process is the phenomenon of springback. This springback phenomenon affects the quality of the sheet metal forming products or components in which it may lead to problems related to assembly process. Furthermore, it has financial impact due to production slowing down and burden of unnecessary rework or rejected products or components cost araising from the springback issues. Nevertheless, these springback issues can be compensated with the use of finite element (FE) method to the extent that it can predict the pattern of occurrence to the product or part. In order to use FE software for the purpose of predicting

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springback in sheet metal forming, the phenomenon should be considered as a complex physical condition that is very sensitive to various factors. Usually, it is very difficult to specify the source of the discrepancy between the magnitude of the springback obtained from an FE simulation and the experimental result, especially when it involves a product with a complex geometry due to the difficulty of achieving accuracy of the stress assessment during the forming process [1–5]. The difficulties of predicting springback using FE method has lead to the trend of incorporating artificial neural network (ANN) in solving the problem. ANN is a mathematical model that attempts to mimic the large number of interconnections of the biological neurons in the human brain to perform a complex processing task. The behaviour of complex experimental data or numerical simulation can be predicted by developing a neural network model with sufficient input data. For past few years, the applications of ANN in the field of sheet metal forming have been used as inverse techniques by utilising FE analysis to predict parameters for established constitutive models. As a matter of fact, ANN as a mathematical model has been widely used to predict a data obtained from a numerical model.

Therefore, this paper discussed and summarized the application of FE and ANN in predicting sheet metal springback. The earlier part of the discussion is focused on the source of the springback phenomena before summarizing the application of ANN in the same field. This is to identify the gap of material's constitutive model and the potential of ANN to be a part of the model. The paper is structured as follows: Section 2 Finite element analysis application of springback in industrial; Section 3 Background of experiments and analysis of springback in sheet metal forming; Section 4 Evolution of the sheet metal elastic properties; Section 5 Nonlinear recovery in springback finite element analysis; Section 6 Soft computing approach; Section 7 Conclusion.

2. Finite element analysis application of springback in industrial

Recent developments indicate that the automotive sector is actively developing efforts to reduce the mass of vehicles to achieve an environmental friendly performance and, at the same time, to improve the safety features in the event of a collision. The main goal of these efforts is to produce a new group of steels with improved formability and with high material strength, namely advanced high strength steel (AHSS). The production of this group of steels, which has a unique microstructure, represents the response of the steel industry to the demand for an improved material based on the needs of the automotive manufacturing sector [6].

The improved capabilities offered by AHSS do not create new forming problems, but instead highlight the problems that have long existed in the forming of other high strength steels, namely the problem of high springback. Generally, springback is caused by elastic recovery, as shown by the stress-strain curve in Fig. 1. Unloading from plastic formation that occurs after all the forces have been released at point *A*, will follow the line *AB* to point *B*, where *OB* is the plastic deformation and *BC* is the elastic deformation. The figure shows that the high stress experienced by the high strength steel produced a greater strain when it experienced elastic recovery compared to lower strength steel. For example, Fig. 2 shows the comparison of the results of the forming of AHSS (DP 350/600) and high strength steel (HSLA 350/450) using the same die. Due to the unequal distribution of strain and elastic strain recovery, the AHSS experienced a higher springback compared to the lower strength steel.

Since the elastic recovery has a significant effect on the springback of the AHSS sheet metal, the accuracy of the Young's modulus

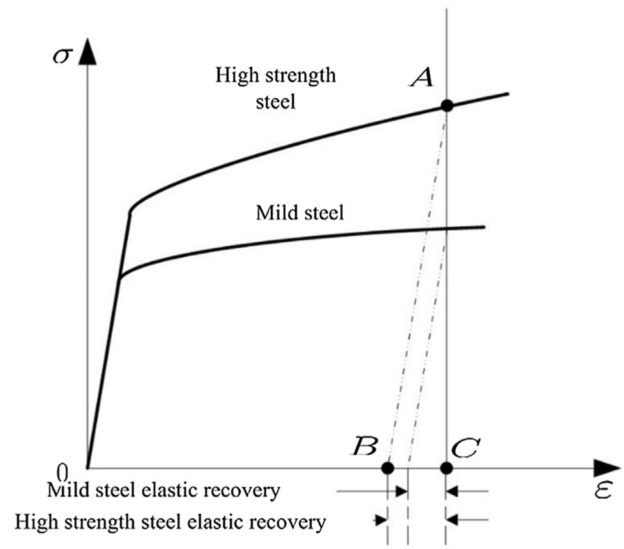

Fig. 1. Schematic of springback that is proportional to the stress level.

should be taken into consideration in the springback prediction. Earlier studies by researchers showed that the unloading modulus was nonlinear and that the assumption of a constant and linear Young's modulus was inaccurate for describing the stress-strain behaviour of materials during unloading after a large plastic strain [8–10]. Through these studies, various methods have been developed to produce a constitutive model that enables FE software to simulate the unloading modulus for the purpose of springback prediction. These include the construction of an additional surface in the yield surface, the elastic-to-plastic transition model, and anisotropic hardening models based on homogeneous yield functions. However, the fact is that the methods that have been developed are rather difficult to put into practice in the software because of the complexity of defining the nonlinear unloading. As such, a linear Young's modulus is still being used extensively in a relative manner for the prediction of springback through FE simulations.

The increase in total springback for high strength sheet metal has caused an increase in the number of errors in the FE software simulation and a reduction in the accuracy of the FE analysis in predicting springback. Although several studies have been conducted on the phenomenon of nonlinear elastic recovery to improve the prediction of springback in sheet metal, the complexity of the material model developed by a number of studies has caused most users of the FE software and researchers to choose the use of linear elastic recovery in the simulation runs. Thus, an easier and more practical programming is needed to facilitate the use of nonlinear elastic recovery in FE analysis. The need provides a wide opportunity for the applications of computational intelligent. However the sustainability of its applications is still weak due to some neglections of engineering knowledge and the dependency of statistical analysis strength of computational intelligent. This literature review is made up of three main parts, starting from a review of experimental methods for springback and changes in the elastic properties of sheet metal to show the research gaps from the engineering point of view. Next, the inadequacy of computational intelligent approaches to fulfil the gaps is presented. In addition, this review describes the aspects of development and advancements in the field to date. This review also focuses on examining the opportunities for advancement in order to contribute to the development and research in this field.

FE analysis has been used in the sheet metal forming industry for the purpose of designing dies for the manufacture of products that approximate the desired design. However, most of the FE sim-

Fig. 2. Two products produced by the same die [7].

ulations have failed to achieve that objective. Therefore, studies on the development and improvement of FE simulations to predict springback in sheet metal have been carried out by researchers, especially on parts that involve the model of the material being used. This is due to the material model factor, which greatly affects the accuracy of the simulation. The stress that is calculated throughout the simulation plays an important role in obtaining results that approximate the experimental data.

Despite the development of material models in FE analysis, several problems that cause errors in the FE simulation results were identified when the material models were applied in simulations of the forming of industrial components. Fig. 3 shows the analysis of the forming of the engine suspension upper bracket conducted by Firat et al. [11] to study the effect of the material model on the FE simulation of springback. The simulation results showed that the springback data were scattered for each measurement path. This made it difficult for the study to remain focused on the effect of the material model because various other factors influenced the stress in the forming process. Eggertsen and Mattiasson [12] outlined several factors that make it difficult to control the stress in the sheet metal structure, starting with the difficulty of controlling the flow of the material into the die based on the pressure exerted on the blankholder. This was due to the pressure distribution that was influenced by the accuracy of the tool's geometry and the friction in the FE simulation.

To simulate the friction between the sheet metal and the tool's surface, the contact penalty formulation is used, where the penetration of several nodes frequently occurs at the contact surfaces. As the number of penetrations is directly proportional to the contact force, it is difficult for the simulation to attain the actual friction experienced by the contact surfaces, thus affecting the stress distribution in the simulation of sheet metal forming. To facilitate the simulation of the forming of industrial components, the tool's surface is assumed to be rigid. However, Eggertsen and Mattiasson [12] stated that deformation takes place in the tool throughout the forming process. It is difficult to take this phenomenon into account in the simulation of the forming of industrial components due to the need to perform measurements or modelling work that are too complex for many industrial products.

Because the stress distribution is influenced by factors that are difficult to control, the material model was developed by focusing on experiments by previous researchers that succeeded in reducing the impact of these factors. The experiments that are frequently used are presented in the following section.

3. Background of experiments and analysis of springback in sheet metal forming

Various experimental techniques and procedures have been developed to analyse and review springback in sheet metal. Among

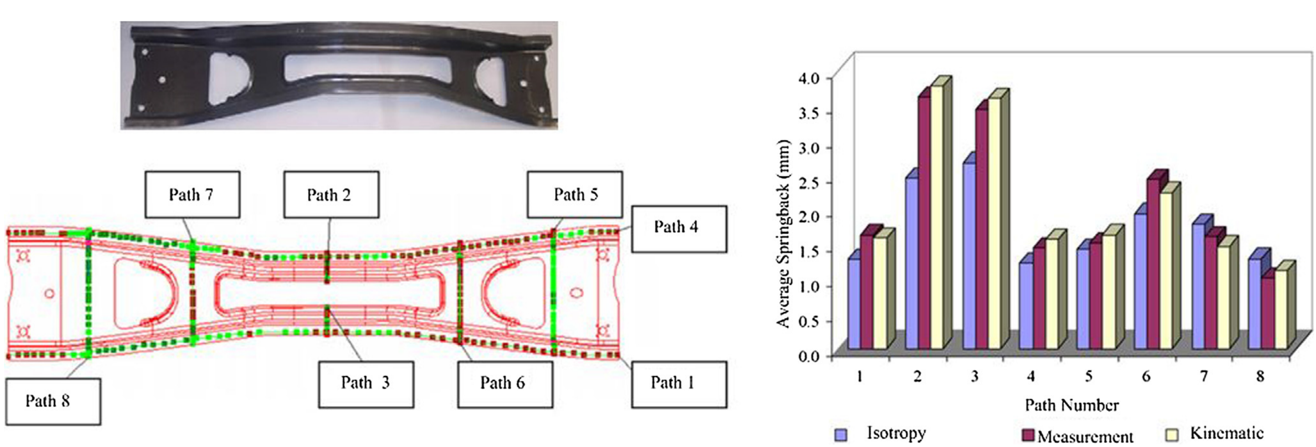

Fig. 3. FE simulation based on an industrial component [11].

the simple techniques that are commonly used are cylindrical tooling [13,14], L-bending [15,16], and V-bending [17,18]. All these methods are interesting because the procedures are simple, and the level of springback in each is easy to apply and measure.

The cylindrical tooling experiment was proposed in the Numisheet 2002 benchmark [19], where the preparation for the experiment is shown in Fig. 4. The punch moves in the die until each is concentric. This method is widely used in studies on the forming and springback of sheet metal due to its simple geometry but complex contact conditions. These features provide a comfortable assessment in terms of the numerical stability and accuracy of the finite element analysis [13]. However, the results of the numerical analysis show that there are several factors that produce a scattered simulation of springback. Among the factors that have been identified are problems with space caused by local sliding contact, difficulty in determining the speed of the punch, and the difficulty of using a stabilization technique on the contact stiffness [20].

Other than cylindrical tooling experiments, V-bending experiments were also carried out by previous researchers, as shown in Fig. 5 [21–24]. When the punch is lowered to form the sheet metal, the properties of the material are separated into two parts, namely the elastic part and the plastic part. The part that comes in contact with the punch experiences compressive stress, while the part that comes in contact with the die experiences tensile stress. Thus, when the punch is raised, the compressed part begins to expand, and the strained part begins to react elastically by shrinking, resulting in springback. This experiment has an initial preparation that is economical and can be built within a large range.

However, the experiment can be affected by the size and speed of the punch, thereby resulting in a negative springback ($\theta_1 > \theta_2$) [25]. In addition, the thickness of the sheet metal and the anisotropy also influence the occurrence of negative springback [23,24]. At the same time, the findings of the experiment are limited to V-bending alone because the sheet metal is formed according to the size of the punch, and often the value of θ_1 is less than 90°. This situation is quite different from the forming of sheet metal in industries, where a die angle of not less than 90° is used. The movement of the punch needs to be controlled as well so as not to excessively compress the sheet metal, which can result in the compression of the bent part, thereby interfering with the measurement of the actual springback angle.

To approximate the industrial process for the forming of sheet metal, the L-bending experiment was carried out to obtain the manufactured part by changing the shape of the sheet metal uniformly on the bending line. Fig. 6 shows the setup for the L-bending experiment conducted by previous researchers [16,26–28]. When the displacement of the punch is increased, the sheet metal comes in contact with the punch and is drawn towards the die. During the bending step, the load on the punch increases rapidly in the initial stage as a result of the total contact surface between the sheet metal and the punch. In the final step of bending, the sheet metal experiences springback based on its elasticity. In terms of the geometry, the reaction of the material or the springback after the punch is moved is influenced by the radius of the die, and the gap between the punch and the die. Although the setup for the L-bending experiment is simple and does not cost much, the springback angle that is produced at the end of the forming process is small. This makes it difficult for researchers, practitioners and engineers to focus the research on the behaviour of the material because the springback angle is easily influenced by the dominance of process parameters such as the gap between the punch and the die, (g) and the radius of the die (R_d).

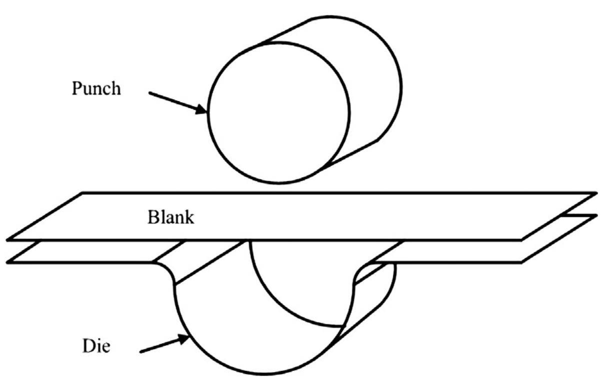

Fig. 4. Initial preparation of cylindrical tooling as suggested in Numisheet 2002 [19].

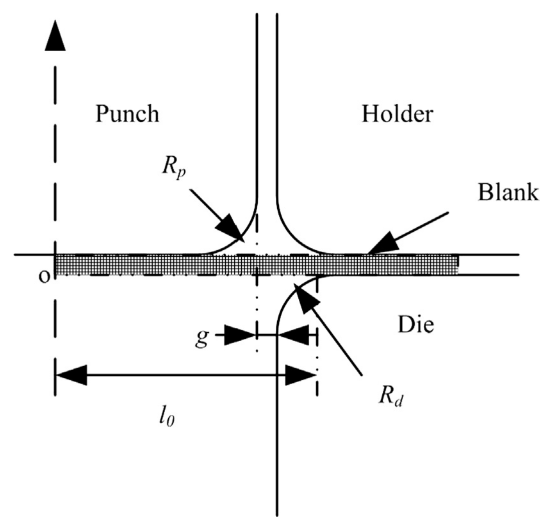

Fig. 6. L-bending test initial setup [16].

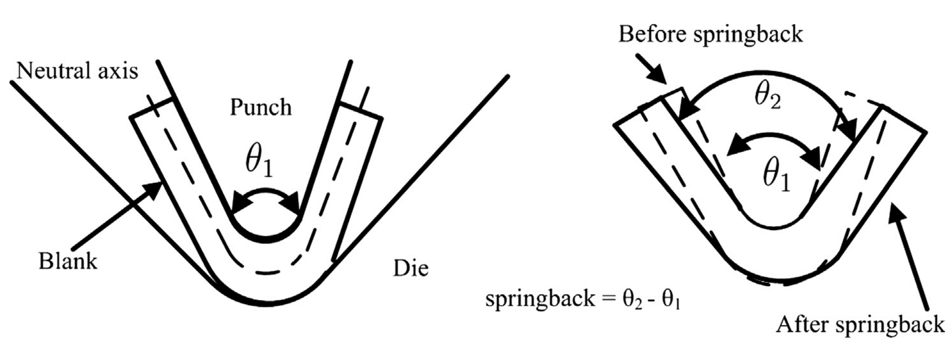

Fig. 5. V-bending test schematic [24].

Although the experiments that have been discussed can be easily conducted, there are drawbacks to each of these experiments, such as the difficulty of simulating the realistic conditions of the process, especially in more complex metal forming processes. All the experiments only involved bending and there was no unbending, as occurs when metal pieces are stretched along the radius of the die. Normally, all these techniques are used to study the basic parameters that are sensitive to springback, such as the ratio (radius of the tool to the thickness of the blank), the geometric parameters of the tool, the mechanical properties of the material, and the friction parameters. The results only have a slight effect, with the existence of a highly significant stress influence on the sheet metal [29]. Due to this situation, a study on the effect of the behaviour of the material on the springback angle cannot be carried out because of more dominant process factors in the production of the springback angle.

In the forming process involving the stretching of the sheet metal in the set die, the material undergoes stretching deformation, bending, and unbending along the radius of the die. To create these conditions, the U-bending-stretching experiment is often used to examine the springback of sheet metal in realistic forming conditions, as shown in Fig. 7. This geometry is used a lot in case studies of springback based on very practical properties, and produces significant springback angles [30–41].

The deformation route experienced by the material yields a complex stress-strain state and subsequently, forms a distinct sidewall curl that can easily be measured, as shown in Fig. 8. However, in that process, the stress of the sheet metal cannot be determined accurately but can only be measured indirectly from the force of the blank holder. This force is dependent on the estimated coefficient of friction. Due to the highly influential role of stress in the sheet metal, the failure to directly control or measure the coefficient of friction represents a serious drawback in the use of scientific experiments that involve the validation of FE simulation techniques.

To overcome the shortcomings in fixing the value of the stress experienced by sheet metal during the stretching process, a draw-bend test was developed to reproduce the springback under mechanical conditions to resemble the practice in industries and, at the same time, to generate the capacity to control the stress in the sheet metal, the radius of the tool, and the contact friction [3]. It was developed from the previous friction test design

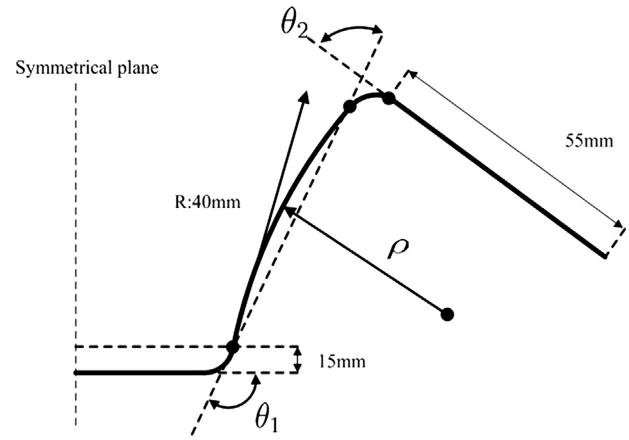

Fig. 8. Springback angle measurement [42].

[43,44]. A metal sheet is formed around a circular tool (roller, representing the radius of the die), as shown in Fig. 9, while the front actuator imposes a constant displacement and the back actuator produces a constant limiting force.

Through this method, the stress in the sheet metal can be fully controlled by the back actuator because the friction at the contact surface of the sheet metal and the circular tool is minimal. The material in the sheet metal is subjected tension, bending, and rebending when it is pulled through the rollers. In the final stage of the experiment, the grip on the sheet is released, thus allowing the sheet metal to undergo springback. This test has been used extensively for experiments on sheet metal springback and related FE simulations [2,3,10,45]. Most of the studies discussed above focused on changes to the elastic properties of the material, which will be described in the next section.

4. Evolution of the sheet metal elastic properties

It has been proven by previous researchers that springback in sheet metal depends on the Young's modulus of the material [46]. In the analysis of sheet metal forming, the Young's modulus is usually regarded as constant. However, some studies have shown that the elastic constant of a material changes following

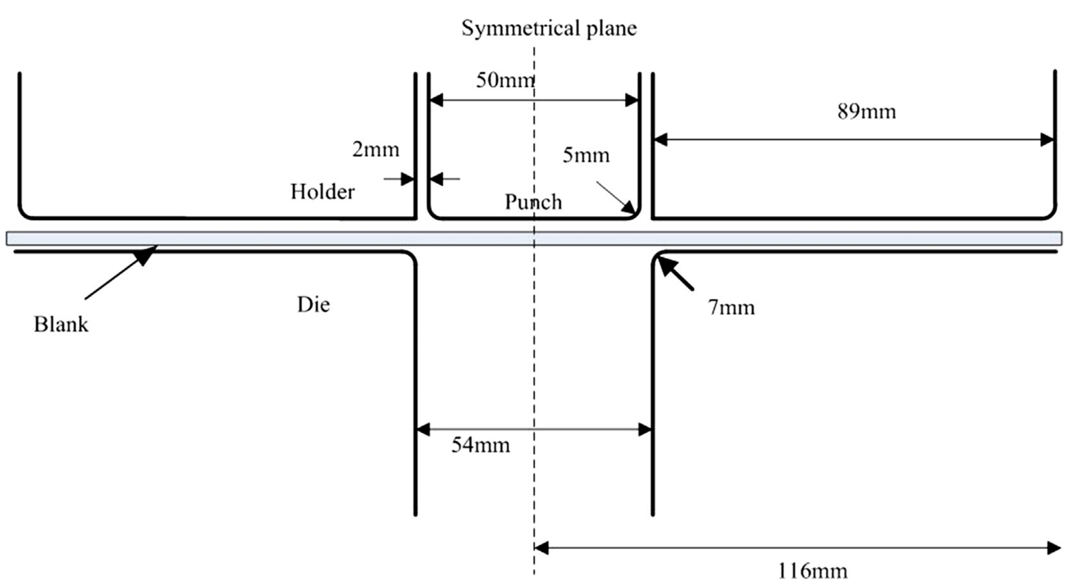

Fig. 7. Schematic view and dimension of 2D draw bend test equipment [42].

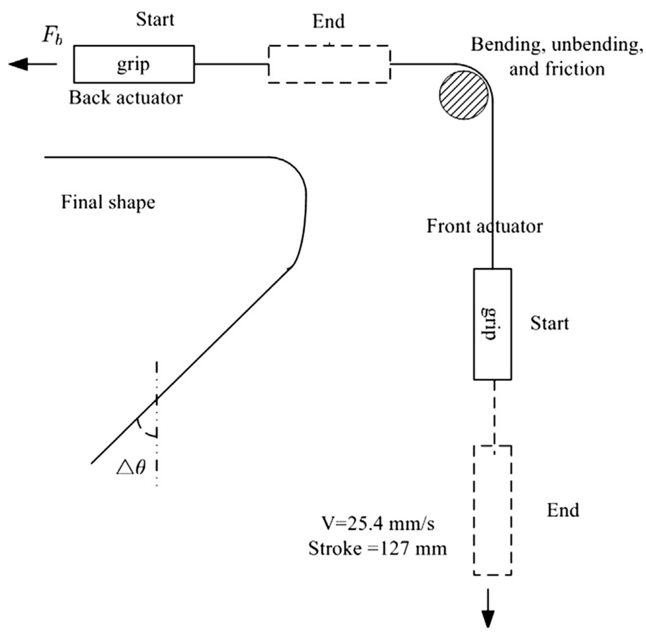

Fig. 9. Schematic of Draw-bend test [10].

plastic deformation. The development of studies into changes to the elasticity of steel is described in the following sub-sections.

4.1. Variable elastic modulus

Studies into the variable elastic modulus of sheet metal were conducted by previous researchers using tension-compression experiments. An experimental method has been developed to produce more accurate experimental results, of which, among the latest developments, is the uniaxial tension-compression test, as shown in Fig. 10. The specimen is marked with a pattern of scattered points for the purpose of measuring the strain in the specimen. A clamp is used to prevent the specimen from buckling when it is compressed. A reinforced Teflon layer is inserted between the specimen and the clamp to eliminate the effects of friction, while a silicon piece is used between the tip of the specimen holder and the clamp to prevent the specimen from buckling. The strain distribution is measured using an optical measurement system.

Significant changes in the Young's modulus for steel and aluminium alloys due to hardening were highlighted by previous researchers [48–52]. Morestin and Boivin [53] studied the changes in the Young's modulus for sheet metal that was influenced by a plastic strain of up to 15%. In his study, a tension-compression testing machine was used to conduct the experiment on a steel specimen. The changes in the Young's modulus and their values when the sample was subjected to stress and compression are shown in Fig. 11. The Young's modulus shrank from 200 GPa to 175 GPa when subjected to a plastic strain of 2%, and remained at that value with further increases in the plastic strain. This showed that with increased hardening activity, attention should be given to changes in the Young's modulus to resemble the actual behaviour in the sheet metal in the analysis of springback, especially in the FE simulation. When the Young's modulus does not change, the error margin can increase up to 19%.

Yang et al. [50] discovered that changes to the Young's modulus after plastic strain are due to the increase in the residual stress and micro cracks, and changes in the structure of the dislocation. The residual stress increases together with the plastic formation and interrupts the elastic recovery, while the increase in micro cracks reduces the density of the material. Fig. 12(a) shows the model of the dislocation collisions, where changes in the structure of the dislocation arise from a common source moving along the same sliding surface, and it easily experiences an overlapping collision because the front dislocation is stopped by barriers such as the grain boundary and solutes. The dislocation collisions move backward when the shear stress is released during the unloading process, as shown in Fig. 12(b). Therefore, the Young's modulus

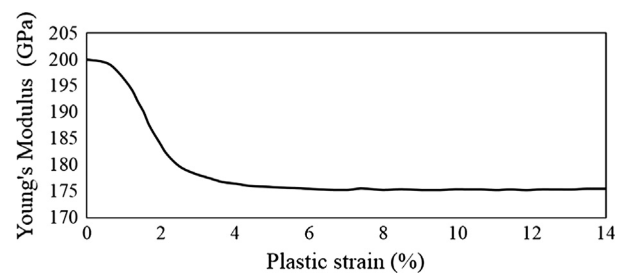

Fig. 11. Young's modulus vs plastic strain [48].

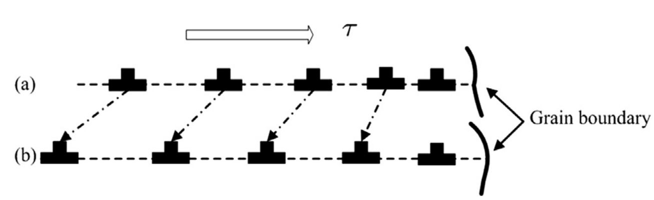

Fig. 12. Dislocation pile-up model; (a) loading; unloading [50].

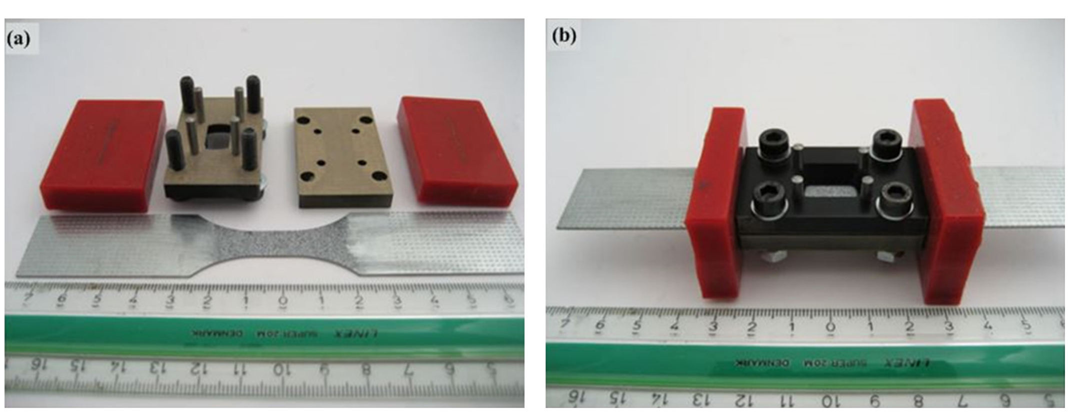

Fig. 10. Experimental apparatus for tension-compression test; (a) dismantled; (b) assembled [47].

decreases due to the increase in the moving dislocations caused by plastic strain.

Other than the magnitude of the plastic strain, the changes to the Young's modulus are also affected by the chemical composition, period of rest after the forming, and the strain path [50,54–56]. For example, the Young's modulus is reduced by up to 30% for mild steel [46,49,57], 20% for high strength steel [46,49,50,55,57,58], and 10% for aluminium [49]. Based on these differences, the changes to the Young's modulus in response to plastic strain were described by Yoshida et al.[59].

By connecting the evolution of the elastic modulus that have been discussed to the forming of sheet metal, the springback prediction can be improved by changing the value of the elastic modulus in the FE simulation [3,9,10,19,60–63]. Morestin et al. [48] proposed an analytical theory approach to springback in steel sheets. Yu and Hai Yan [64] used a quadratic polynomial to describe the difference in the elastic modulus of TRIP steel, and applied it to solve the experimental U-bend-slide springback. Both macroscopic and microscopic measurements were carried out by Yang et al. [50], who examined the changes in the V-bending elastic modulus and springback of cold-rolled SPCE sheet metal. All the above studies showed that the prediction of springback can be improved by taking into account changes in the elastic modulus. This was also proven by several other studies that reported the same findings as the studies into the forming of TRIP700 and TRIP800 pieces [55], V-bending TRIP steel pieces [54], bend-stretch AA2024-T3 aluminium pieces [60], and draw-bend DP600 column pieces [45].

Although the chord modulus can be used to improve the results of the springback simulation, it is unable to describe the nonlinearity of the unloading process. This is because the chord modulus only connects the yield stress point and the zero stress point by a straight line, while both points need to be connected by a nonlinear line. To obtain a more accurate springback simulation, the simplified nonlinear recovery is only adequate if the springback phase reaches full contraction. Generally, although, in the springback phase, the stress that is produced in the forming phase decreases, it still remains as residual stress. This condition confirms the need for the modelling of nonlinear elastic recovery in the prediction of springback [9]. A description of nonlinear elastic recovery is presented in the next subsection.

4.2. Nonlinear elastic recovery

In elastoplastic constitutive modelling, the Young's modulus is often regarded as a constant, even after undergoing plastic formation. However, several experimental observations have indicated that metallic materials, including steel and aluminium alloys, differ in linearity, i.e. they form hysteretic loops during unloading and reloading. This relationship is known as nonlinear elastic recovery, as shown in Fig. 13. After plastic formation up to point *A*, the unloading process begins at point *A* and ends at point *C*, based on the initial elastic modulus that represents the linear elastic recovery. If the chord modulus is applied to the unloading process, the elastic recovery will end at point *B*.

Andar et al. [8] measured the difference in the elastic modulus for BH340 and DP590 steel under uniaxial and biaxial conditions. The study found that at the initial stage, the elastic modulus shrank rapidly according to the plastic deformation, where the shrinkage varied according to the material. Various mechanisms for nonlinear unloading behaviour due to plastic deformation have been proposed such as residual stress [65], anelasticity [66,67], damage evolution [68,69], kink-bands in HCP alloys [70–72], and stacked collisions as well as the relaxation of dislocation arrays [49,50,53,58].

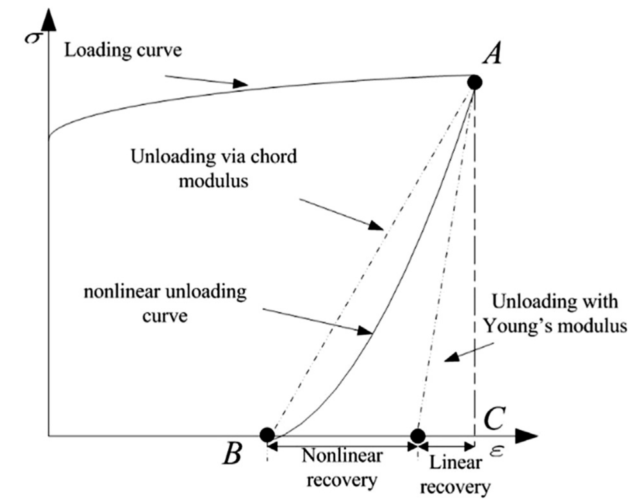

Fig. 13. Stress-strain curves for linear and nonlinear unloading [73].

In the tension-compression test, if the specimen undergoing unloading is subjected to reloading, the flow curve will be in the form of a closed loop, as shown in Fig. 14. The width of this loop increases with an increase in the plastic strain during the plastic forming process, where the area of the loop represents the amount of dissipated work. This loop is reversible for low cycles. Compared to a monotonic flow curve, the plastic behaviour as a whole is not affected by the loading and unloading cycles [70].

Through Fig. 14, Govik et al. [74] mapped the instantaneous tangent modulus in Fig. 15 to illustrate more clearly the nonlinear nature of the unloading. The researchers discovered that there was no part on the unloading curve that was linear in nature. At the same time, for a pre-strain higher than two percent, the nonlinear nature was the same between one another, while the elastic modulus decreased with increasing pre-strain.

5. Nonlinear recovery in springback finite element analysis

Although the nonlinear recovery experimentally shows a small amount of strain deviation, its effect on a total sheet metal forming simulation is significant due to mechanical reproduction of every element [75]. The influence can be understood by referring to the stress-strain profile produced from the whole simulation in Fig. 16, where the stress-strain value represents the profile of one single element of the sheet metal blank in the draw-bend test. The fluctuation of tension and compression is explained in a sche-

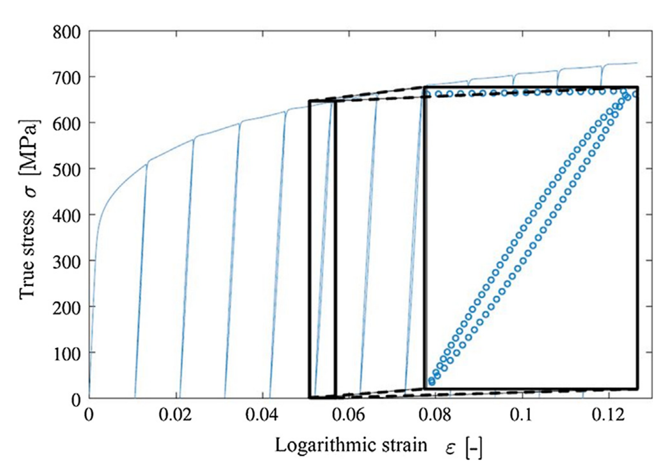

Fig. 14. Uniaxial cyclic test results [74].

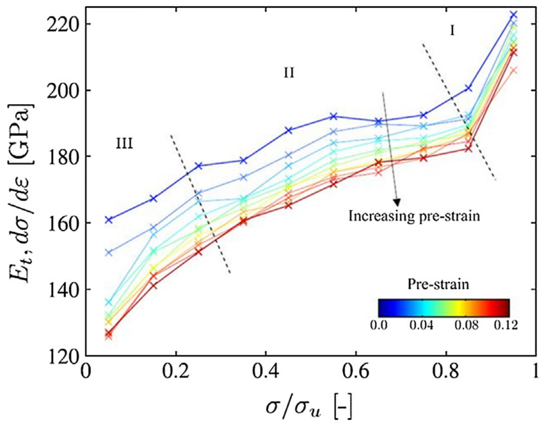

Fig. 15. Instantaneous tangent modulus vs normalized stress during unloading.

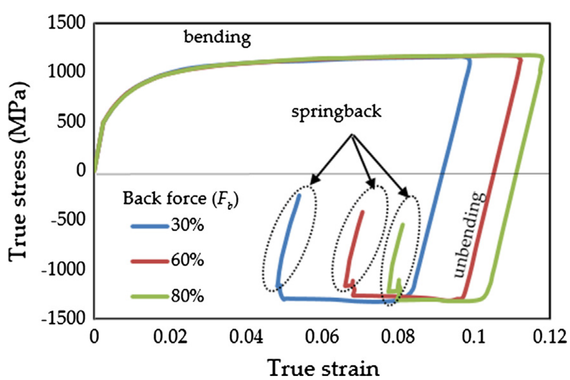

Fig. 16. Variation of stress value in the draw-bend test simulation [75].

matic of stress variation in the sheet metal blank, as shown in Fig. 17. In the initial step of draw-bending, sheet metal blank will experience elastic deformation before passing through the rotating cylinder. Through the drawing process, the blank is subjected to bending and plastic deformation at the rotating cylinder. After passing through the rotating cylinder, the element in the blank experiencing unbending due the blank straightening. At the end of the drawing process, the load on the blank was released which leads to the occurrence of springback in which the stress of each element reduced elastically.

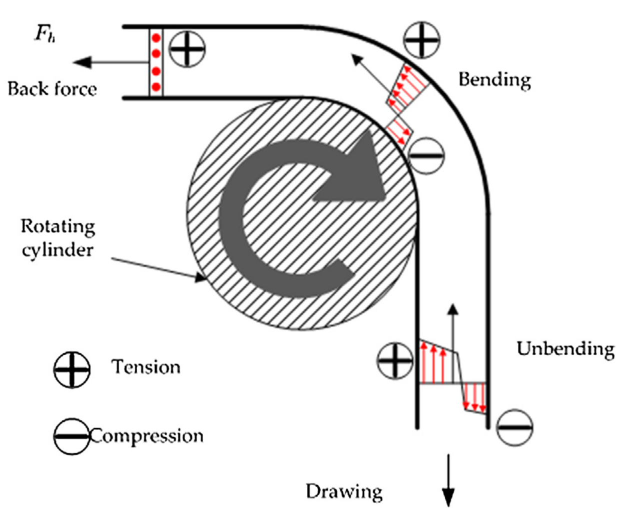

Fig. 17. Schematic of stress variation in the sheet metal blank [76].

Based on the stress-strain profile, it can be seen that the stress value at the end of springback process remains as residual stress and the unloading path form a curve. The value of residual stress in each element depends on its strain path. Therefore, it is essential to include nonlinear elastic recovery to represent sheet metal springback. However, the unloading process utilize the change of elastic strain, which is linear in a standard finite element software. This prompted other researchers to develop modelling methods in FE software to obtain simulations that mimic the behaviour of actual materials. Torkabadi et al. [77,78] developed a model for describing the nonlinear unloading behaviour by quantifying the anelastic strain. Eggertsen and Mattiasson [79] developed an additional surface in the yield surface, while Sun and Wagoner [10] developed an elastic-to-plastic transition model to describe the nonlinear recovery in a constitutive model. Lee et al. [80] developed an anisotropic hardening model based on a homogeneous yield function for the same purpose. All these models increased the computational cost [81] and difficulties are experienced by other researchers because of the complexity of reconstructing the model. Because of this factor, the use of the elastic modulus as a linear variable is more widely accepted in applications for springback prediction [77]. To overcome this problem, software computation approach is having the potential to be integrated with the FE material constitutive model. However, the integration shall utilize the capability of artificial intelligence in predicting the experimental data and provides input to FE software. The next section describes the previously practice software computation approach, which has become the alternative to the complex constitutive modelling in FE analysis.

6. Soft computing approach

The definition for soft computing was introduced in the early 90 s in the field of computer science to refer to the combination of two or more computerised methods to solve problems that are difficult to predict. This approach, by Warren McCulloch and Walter [82], was the result of the development of artificial intelligence in 1943. Initially, this approach performed precision modelling and analysis on simple systems. But lately, many complex systems have been developed in various fields such as biology, medicine, management science, and engineering. This approach is needed to overcome problems that are difficult to solve using conventional mathematics and analytical methods. Among the components that are included in the software computation approach are artificial neural networks (ANN), fuzzy logic, genetic algorithms (GA) and particle swarm optimization (PSO).

One of the main purposes of using the software computation approach, same as the purpose of using FE analysis, is to reduce the number of experiments to determine the behaviour patterns of materials or processes. To achieve that objective, several studies carried out on springback in the forming of sheet metal only made predictions directly from experimental measurements. This approach was often used as an alternative to FE analysis [83]. The same approach was also used for solving the issue of springback in sheet metal.

Narayanasamy and Padmanabhan [84] compared the ability to predict springback in interstitial-free metal sheets in the air bending process by regression modelling and ANN. With the results by both models approaching the actual springback measurements, the ANN prediction technique was found to be better than the regression analysis. Baseri et al., [85] developed an fuzzy back propagation learning algorithm to predict springback in sheet metal in a V-bending process based on data generated by experimental observation. The algorithm predicted the springback, which was measured based on three different parameters, namely the punch tip radius, the thickness, and orientation of the sheet metal. With the prediction results approaching the experimental data, the developed model was able to show the relationship between the springback and the input parameters in the V-bending process.

Direct ANN predictions from the experimental measurements still continue until recently in the field of metal forming as well as in other engineering fields [86–89]. This method enables researchers to overcome the complexities involved in studying the behaviour of materials, while at the same time, ignoring all the theories and processes involved, as shown in Fig. 18. A large amount of experimental data is required to improve the accuracy of the prediction, and this will increase the cost of the experiment. The number of process parameters for the prediction must also be limited because a high number of process parameters will increase the number of experiments that have to be carried out. The relationship between the process parameters and the final product that is generated can only be used for the prediction process and lies within the prediction range only. Fig. 19 shows the strain profile prediction architecture of sheet metal in terms of the change in behaviour of the material before the forming process by Veera Babu et al.[90]. In that study, various parameters were not used as inputs to the ANN such as the die friction, die radius, punch speed, and so on. In the event of changes to these parameters, the prediction has to be performed again and the experimental and computational costs will rise. As a result, the study being conducted will lack continuity, and the same procedure will have to be repeated for different problems.

The ANN approach was also used to build a constitutive model and its accuracy was compared to the constitutive model that had been developed earlier. In recent years, there have been a few studies regarding the application of ANN to build elaborate constitutive models, as shown in Fig. 20. Such studies ended without the implementation of any ANN-based constitutive model in the FE code. Forcellese et al. [91] developed a multi-variate ANN-based empirical model that was able to predict the flow curve and the metal forming limit curve for magnesium AZ31 in hot forming conditions. The model maps the effects of temperature, strain rate and fibre orientation on the flow curve and the stress without the key knowledge about the mechanism of the complex microstructure that is taking place in the heat forming. Similar studies were also carried out in other fields of metal formation such as forging [92], isothermal compression [93–96], and hot forming [97–99]. However, the constitutive ANN model developed has not been used in FE simulations, and the research pattern to date is only to repeat the same procedure for different materials [100–108].

Therefore, many attempts have been made by researchers to combine FE and ANN to maximise the benefits of each approach, mainly to reduce the experimental costs and to improve the accu-

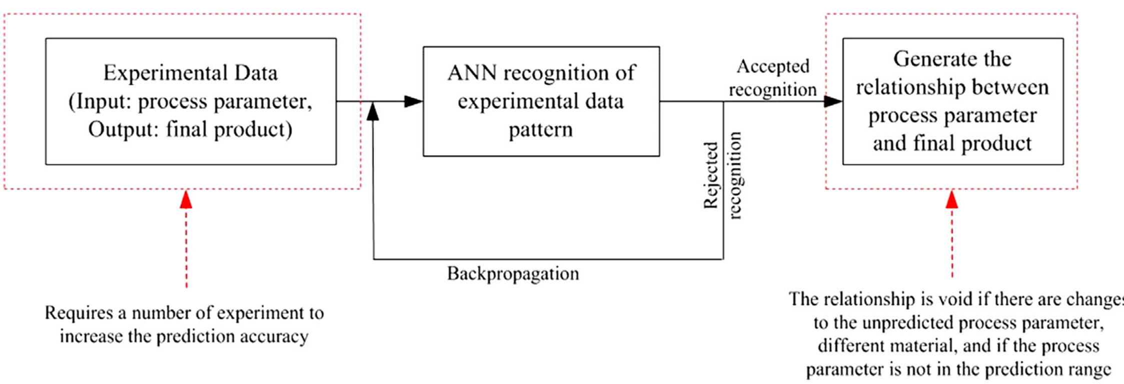

Fig. 18. ANN prediction of the experimental data.

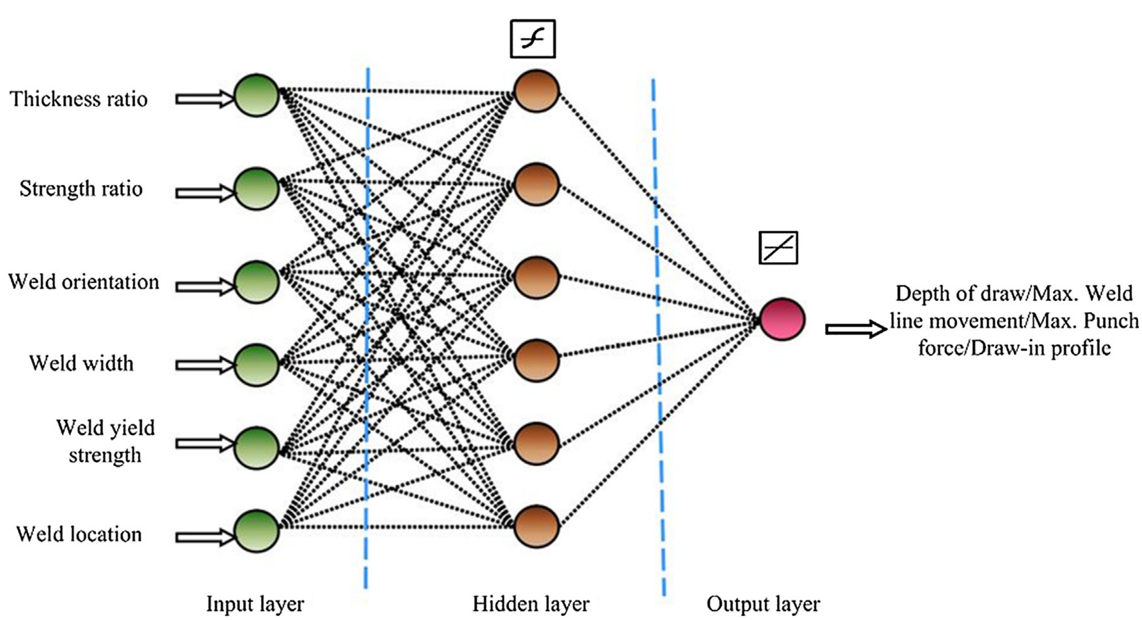

Fig. 19. Neural network architecture for deep drawing behavior prediction [90].

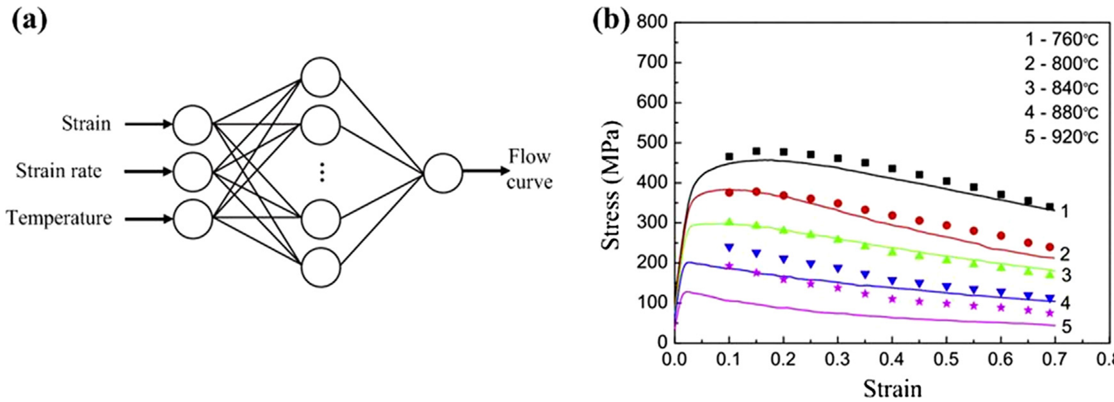

Fig. 20. Application of ANN to predict material properties; (a) ANN architecture; (b) prediction results [104].

racy of the prediction [109–115]. From the initial approach until recently, most studies in relation to the integration of ANN and FE for solving engineering problems only used the inverse analysis with the aim of optimizing the FE simulation parameters, as shown in Figs. 21 and 22. In those studies, the researchers conducted a number of FE simulations with different parameters. A small number of simulations were separated and compared with the experimental results for the purpose of validation. A comparison of the results showed that the FE simulation results approached the experimental results. Hence, researchers have assumed that the entire FE simulation resembles the actual behaviour in the laboratory experiments. Therefore, the ANN prediction was carried out using different parameters for the overall FE simulation as the input data to the ANN. In turn, the FE simulation results were used as the output data to the network, thereby ignoring any experimental data. Here, there was doubt as to the necessity of using the ANN because the FE simulation that was conducted was assumed to have solved any problems with the simulation.

This method was also used by researchers to solve problems concerning the forming of sheet metal. Chamekh et al. [117] proposed a method to identify the anisotropic Hill parameters from a cylindrical cup stretching experiment. The ANN model was trained based on information obtained from a finite element simulation. The parameter values were calibrated by minimizing the difference between the curves for the change in the thickness of the metal piece obtained from the ANN prediction and the finite element simulation. The proposed ANN model was able to build an approximate function for the minimal thickness depending on the material parameters and the coefficient of friction. Aguir et al.[118] suggested a hybrid optimization strategy that combines the FEM, ANN, and GA. In their study, the parameters for Voce's law as well as Karafillis and Boyce's criterion for stainless steel were predicted based on a tension and bulge test. To reduce the number of simulations, some FE simulations were replaced by the ANN model in the optimization loop. The low number of simulations resulted in a shorter computation period compared to the classical inverse method. All the studies succeeded in predicting the parameters to produce optimum FE simulation results. [116,119,120].

Although the use of the ANN is able to reduce the gap between the FE simulation and the experimental data, the approach is still influenced by a number of shortcomings. In the context of the properties of the material, the simulation results obtained depend on the ability of the constitutive model of the material. Therefore, the prediction results that are generated remain within the sphere of the constitutive model available in the FE software. This causes the parameters identified by the ANN to represent only the FE simulation behaviour based on the constitutive model rather than the actual behaviour of the material involved in the engineering analysis.

The inverse analysis between FE and ANN only focuses on the prediction of physical parameters, while the results of the FE simulation are influenced by both the physical and numerical parameters. The numerical parameters in the FE analysis include the mesh density, types of elements, contact description, and integration schemes. If these numerical parameters or the entire FE model were to change, this ANN prediction model developed by inverse analysis cannot be used anymore. Therefore, the inverse analysis is repeated continuously each time there is a new FE simulation model, where it contributes to incoherence in the inverse FE and ANN analyses in solving engineering problems [121–124]. In some other researches, the inverse analysis is only considered as a statistical method or technique, where the entire prediction process is focussing on the FE results only, as shown in Fig. 23 [125,126]. In the related studies in the figure, the ANN training data were taken entirely from the parameter changes in the FE simulation in order to study the sensitivity of the parameters towards the simulation results. Therefore, the ANN was only used to map the software behaviour rather than the behaviour of the material being studied.

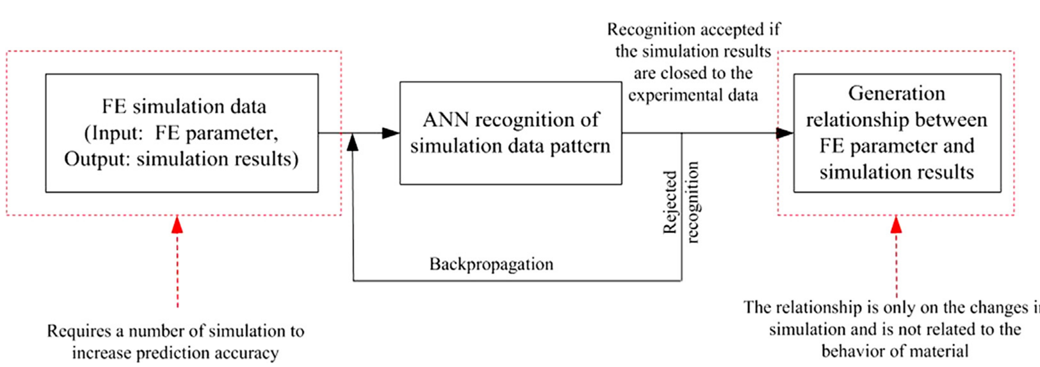

Fig. 21. ANN prediction of the FE simulation data.

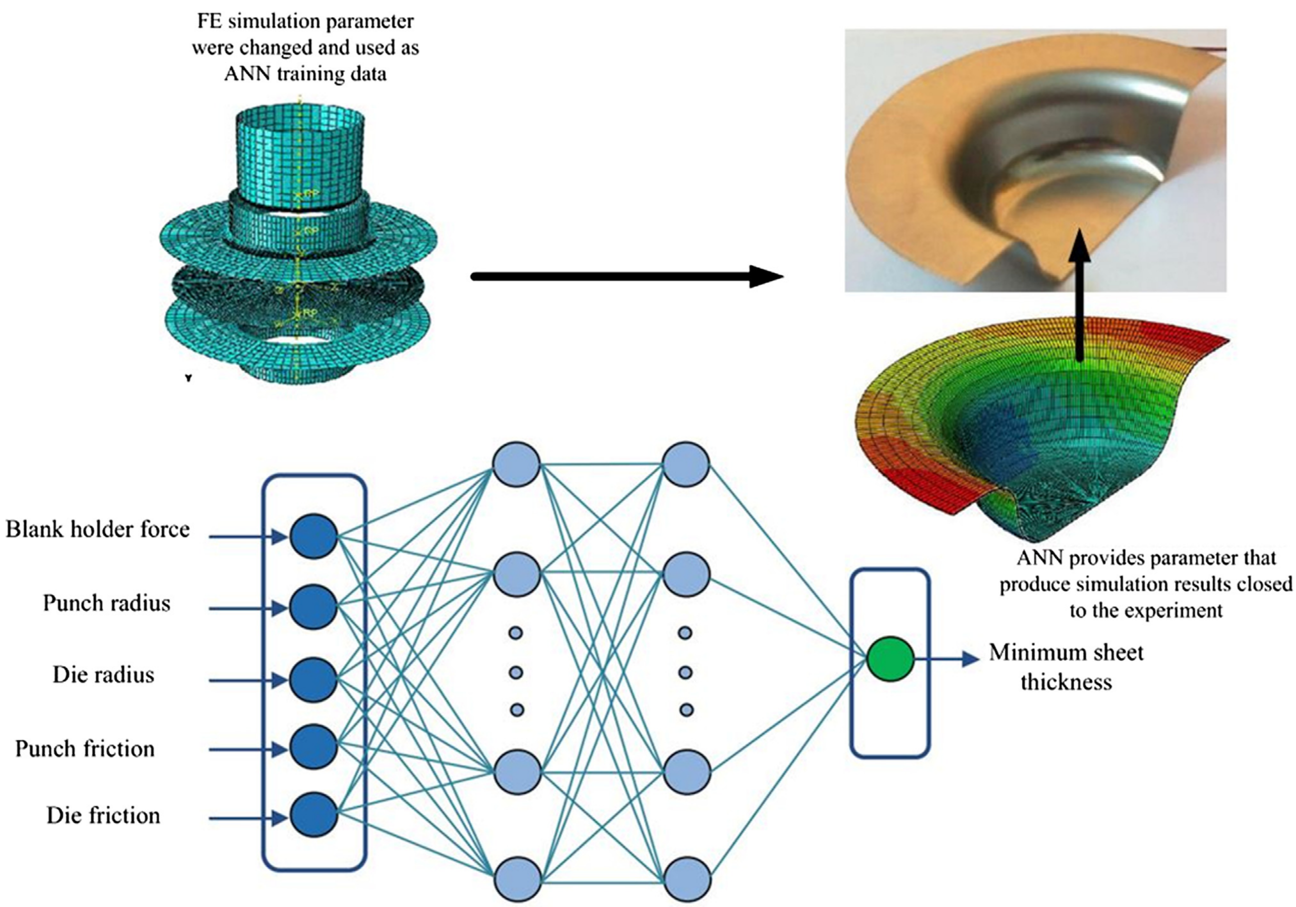

Fig. 22. ANN inverse analysis of FE simulation [116].

A summary of literature review of ANN used to predict FE software results is listed in Table 1.

Despite distinct number of ANN-inverse analysis to solve sheet metal springback, Jamli et al [137] has extensively investigated the capability of neural network to predict the nonlinear unloading for pre-strained steel sheet and the springback of the draw-bend test through FE analysis. The research demonstrated the application of ANN as a part of a constitutive model in FE code. In addition, the application indicates the significance of emphasising the non-linearity of the unloading modulus instead of the chord modulus,

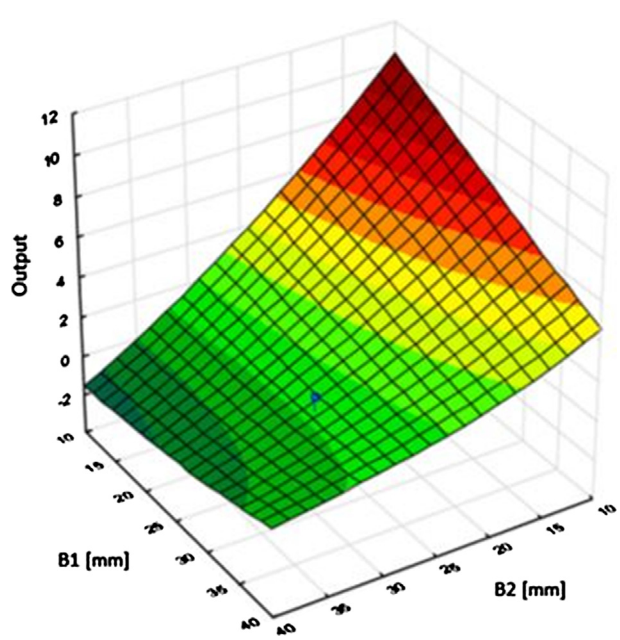

Fig. 23. FE parameter sensitivity prediction [125].

Table 1
Summary of literature review of ANN used to predict FE software results.

No.	Forming process	Prediction technique	References
1.	V-bending	Knowledge-based neural network	[127]
2.	U-bending	Back-propagation neural network	[128]
3.	Cold bending	Back-propagation neural network	[129]
4.	Wipe bending	Back-propagation neural network	[130]
5.	Roll forming	Knowledge-based neural network	[131]
6.	Air bending	Neural network metamodelling	[132]
7.	Incremental forming	Particle swarm optimization neural network	[133]
8.	Tube bending	Multilayer perceptron	[134]
9.	Roll bending	Multilayer perceptron	[135]
10.	Air bending	Back-propagation neural network	[136]

Table 2
Springback prediction with different unloading modulus [137].

F_b	0.3	0.6	0.8	$< \sigma >$
Experiment [10]	63.5°	53.9°	45.9°	0
ANN + FEM	67.6°	55.46°	47.4°	2.68
FEM: Young's modulus	57.7°	49.35°	42.52°	4.68
FEM: Chord modulus	82.06°	67.66°	58.31°	15.14

as the final product of springback contains residual stresses. With an appropriate neural network architecture, the FE prediction has the capability to closely resemble available experimental data by previous researchers. Table 2 shows the results of springback prediction with different method of unloading modulus.

7. Conclusion

A summary of the literature review and its findings is given below:

- The stretch-bending test is the best test of springback in sheet metal to control the stress during the forming process and to produce a significant springback angle to facilitate the measurement of the angle.
- Nonlinear elastic recovery has a significant impact on the springback angle in the forming of high strength steel, where the springback cannot be predicted accurately if the phenomenon is not taken into account in the FE simulation.
- The development of a constitutive model that describes the phenomenon of nonlinear recovery is rather complicated compared to the existing constitutive model. This makes it difficult for other researchers to use it in studies related to nonlinear elastic recovery.
- The complexity of building a constitutive model has opened up opportunities for the development of the ANN to map the behaviour of materials. However, the mapping does not apply to the use of FE for complex simulations.
- The combination of the ANN and FE in an inverse analysis proved to be successful in reducing the gap between the experimental and the FE simulation results. However, this method still has several drawbacks in that it only assesses the effects of parameter changes on the analysis results, fails to represent nonlinear behaviour in materials because it uses the material models that are available in the FE software, and requires a large number of simulations to prepare the ANN training data.
- The construction of a constitutive model based on the ANN in user-defined subroutines in the FE software has the potential to generate a more accurate simulation of springback in sheet metal.

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