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Prediction of static recrystallization in a multi-pass hot deformed low-alloy steel using artificial neural network

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ABSTRACT

The static recrystallization behaviors in 42CrMo steel were investigated by isothermal interrupted hot compression tests. Based on the experimental results, an efficient artificial neural network (ANN) model was developed to predict the flow stress and static recrystallized fractions. The effects of the deformation temperature, strain rate and deformation degree, as well as initial grain sizes, on the static recrystallization behaviors in two-pass hot compressed 42CrMo steel were investigated by the experiments and ANN model. A very good correlation between the experimental and predicted results from the developed ANN model has been obtained, which indicates that the excellent capability of the developed ANN model to predict the flow stress level and static recrystallization behaviors in two-pass hot deformed 42CrMo steel. The effects of strain rate, deformation temperature and degree of deformation on the static recrystallization behaviors are significant, while those of the initial austenite grain size are slight.

1. Introduction

The hot rolling and forging processes often consist of several successive deformation stages, including inter-pass periods between deformations. During the inter-pass periods, the metals and alloys will subject to the dynamic recovery, static recrystallization (Fernández et al., 2000; Lin et al., 2008e), and metadynamic recrystallization (Elwazri et al., 2004). Meanwhile, the materials are often subjected to complex time, strain, strain-rate, and temperature histories in industrial forming processes. On the one hand, a given combination of thermo-mechanical parameters yields a particular metallurgical phenomenon (Lin et al., 2008a), including the microstructural evolution during the inter-pass periods; on the other hand, microstructural changes of the metal in turn affect the mechanical characteristics of the metal such as the flow stress, and hence influence the forming process. Therefore, the constitutive flow behaviors and microstructural evolution of materials, especially in multi-pass processing, is quite complex in nature. In the past, some researchers carried out many investigations about these issues. Poliak and Jonas (2004) predicted the inter-pass softening from the strain-hardening rate prior to unloading. Also, they eliminated the need to determine the retained strain to predict the softening kinetics in multi-hit deformation and simplified the extrapolation of laboratory data to the conditions of industrial processing. Lee et al. (2007) studied the flow softening behavior during high-temperature deformation of AZ31Mg alloy. He et al. (2008a, 2009) investigated the effects of deformation temperature and strain rate on the hot deformation behaviors of as-cast Ti–45Al–8.5Nb–(W, B, Y) alloy, and a neural network model was established to predict the flow stress of this high-Nb containing TiAl-based alloy during hot deformation. Also, a mathematical model to predict the stress–strain curves of this high-Nb containing TiAl-based alloy during hot deformation were developed (He et al., 2009). A method to predict flow stress considering dynamic recrystallization (DRX) during hot deformation was presented, and the flow stress constitutive equations of magnesium alloy AZ31B and 42CrMo steel during hot deformation were developed using the proposed method by He et al. (2008b). Toloui and Serajzadeh (2007) developed an integrated mathematical model to predict distributions of temperature, strain and strain rate during hot rolling as well as the subsequent microstructural changes after hot deformation. Through comparing the model predictions with the experimental results the performance of the model was proved for single stand hot rolling of AA5083 aluminum alloy. In order to achieve the desired mechanical properties of the product, understandings of microstructural changes and softening mechanisms taking place during the complex forming processes are vital for designers of metal forming processes (Rao et al., 1998). The conventional methods are to carry out the regression analysis based on the experimental results, in order to obtain the constants in the classical models. However, the response of the deformation behaviors of the materials under elevated temperatures and

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strain rates is highly nonlinear, and many factors affecting the flow stress are also nonlinear, which make the accuracy of the flow stress predicted by the regression methods low and the applicable range limited (Lin et al., 2008f). However, the field of neural networks can be thought of as being related to artificial intelligence, machine learning, parallel processing, statistics, and other fields. The attraction of artificial neural networks (ANNs) is that they are best suited to solving the problems that are the most difficult to solve by traditional computational methods. Neural networks can provide a fundamentally different approach to materials modeling and material processing control techniques than statistical or numerical methods. One of the main advantages of this approach is that it is not necessary to postulate a mathematical model at first or identify its parameters using a neural network. Some efforts have been made to the applications of neural networks in industry or academic study. Downes and Hartley (2006) developed a technique using an artificial neural network to assist in the design of roll-forming tools. Capdevila et al. (2006) studied the influence of processing on strength and ductility of automotive low-carbon sheet steels using neural network analysis method. Eyercioglu et al. (2008) predicted the martensite start (Ms) and austenite start (As) temperatures of Fe-based shape memory alloys (SMAs) using a back-propagation ANN that uses gradient descent learning algorithm. Peng et al. (2008) introduces a new method for strip shape control. It takes two steps: the first step is to use an ANN to recognize the strip shape pattern. The second step is to apply one or a combination of several controls accordingly. This process may take several iterative steps. Sheikh and Serajzadeh (2008) used neural networks for estimation of flow stress of AA5083 with regard to dynamic strain ageing that occurs in certain deformation conditions and varies flow stress behavior of the metal being deformed.

42CrMo (American grade: AISI 4140) is one of the representative medium carbon and low-alloy steel. Due to its good balance of strength, toughness and wear resistance, 42CrMo high-strength steel is widely used for many general purpose parts including automotive crankshaft, rams, spindles, etc. In the past, many investigations have been carried out on the behaviors of 42CrMo steel. The flow stress constitutive equations, depicting the work hardening-dynamical recovery and dynamical recrystallization, were established (Lin et al., 2008b). A revised model describing the relationships of the flow stress, strain rate and temperature of 42CrMo steel at elevated temperatures is proposed by compensation of strain and strain rate (Lin et al., 2008c). Lin et al. (2008d) carried out the numerical simulation for stress/strain distribution and microstructural evolution in 42CrMo steel during hot upsetting process. The kinetics equations of static recrystallization in the hot deformed 42CrMo steel to predict the softening behaviors induced by static recrystallization were developed by Lin et al. (2008e). Despite large amount of efforts invested into the behaviors of 42CrMo steel, the effects of hot forming processing parameters on the microstructures of hot deformed 42CrMo steel need to be further investigated to study the workability and establish the optimum hot forming processing parameters. Despite large amount of efforts invested into the behaviors of 42CrMo steel, the kinetics of static recrystallization in the hot deformed 42CrMo steel still need to be further investigated to study the workability and optimize the hot forming processing parameters.

In this study, the static recrystallization behaviors in 42CrMo steel were investigated by isothermal interrupted hot compression tests. An efficient ANN model was developed to predict the static recrystallized fractions and investigate the effects of deformation parameters on static recrystallization behaviors in the hot deformed 42CrMo steel. Comparisons between the experimental and predicted results were carried out.

2. Experiments

A commercial 42CrMo high-strength steel of compositions (wt.%) 0.450C–0.280Si–0.960Cr–0.630Mn–0.190Mo–0.016P–0.012S–0.014Cu–(bal.)Fe was used in this investigation. Cylindrical specimens were machined with a diameter of 10 mm and a height of 12 mm. In order to minimize the frictions between the specimens and die during hot deformation, the flat ends of the specimen were recessed to a depth of 0.1 mm to entrap the lubricant of graphite mixed with machine oil. To study the progress of static recrystallization, two-pass hot compression tests were performed on a computer-controlled, servo-hydraulic Gleeble-1500 thermo-simulation machine. It can be programmed to simulate both thermal and mechanical industrial process variables for a wide range of hot-deformation conditions.

The specimens were heated to 1200 °C at a heating rate of 10 °C/s and held for 5 min. Then, the specimens were cooled to the deformation temperature at 10 °C/s and held for 1 min to eliminate thermal gradients. Four different deformation temperatures (850, 950, 1050 and 1150 °C) and four different strain rates (0.01, 0.1, 0.5 and 1 s^{-1}) were used in two-pass hot compression tests. In order to investigate the effects of deformation degree on the softening behaviors, three different deformation degrees (a reduction of 5%, 10% and 15% in specimen height) were applied. Of course, it should be keep the first deformation was interrupted below the critical strain required for dynamic recrystallization in order to avoid the dynamic recrystallization. Then, the static recrystallization would occur in the unloading period (inter-pass). The critical strains had been reported elsewhere (Lin et al., 2008b, c). The deformation temperatures, strain rates and the deformation degrees are same for the first and second deformations. During the inter-pass periods, the specimens were held at the deformation temperature for delay time of 1–100 s to enable static recrystallization to progress. A second deformation was then applied to measure the amount of softening, and then the specimens were rapidly quenched in water. Fig. 1 shows the typical true stress–strain curves obtained from two-pass hot compression tests of 42CrMo steel for different inter-pass delay time (under deformation temperature of 950 °C, strain rate of 0.1 $s^{-1}$and deformation degree of 15%). It can be easily found that given the same heat treatment history and deformation schedule, the yield stress of the second deformation generally decreases as the inter-pass delay time is increased. Similar results were obtained under other test conditions.

3. Development of ANN model for flow stress prediction

3.1. Theory of artificial neural network (ANN)

ANNs are a large class of parallel processing architectures, which can mimic complex and nonlinear relationships through the appli-

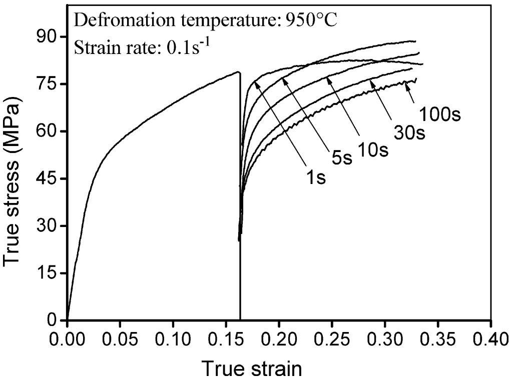

Fig. 1. Typical true stress–strain curves vs. inter-pass delay time.