A screening strategy for hot forging combining high-throughput forging experiment and machine learning

Zhiren Sun and Kaikun Wang
University of Science and Technology Beijing, Beijing 100083, People’s Republic of China
E-mail: kkwang@mater.ustb.edu.cn

Keywords: hot forging, machine learning, high-throughput experiment, IN718

Abstract
In this study, we proposed a screening strategy of processing conditions for hot forging based on high-throughput experiment equipment, numerical simulation, and machine learning to obtain the optimal conditions for the forging process. Nickel based superalloy IN718 was selected as an application case. We designed high-throughput experiment equipment for hot forging. Numerical simulation of the forging process on the equipment was studied, and a database of 625 examples was obtained. Two BP NN models for average grain size and maximum principal stress predictions, respectively, were trained. These two BP NN models were used to search different processing conditions in searching space consisting of 1 206 000 processing conditions, and an algorithm was designed to screen the processing conditions comprehensively considering the average grain size and the maximum principal stress in the bulge zone. The optimal conditions for different forging displacements were obtained. Compared with the traditional high-cost and time-consuming trial-and-error methods, the method proposed in this paper to optimize the processing technology has significant advantages. This method can be applied to pre-screening for material design and process optimization.

1. Introduction
Hot forging is a very efficient way to perform metal parts quickly and at low cost. It also plays a significant role in controlling and optimizing the grain size of metal materials, and thus can improve the mechanical properties of the metal material substantially [1]. In other words, a better processing condition will lead to better properties. A large number of ‘trial-and-error’ experiments should be carried out to identify the optimal processing conditions, which is costly and time-consuming. Therefore, we designed high-throughput equipment combining the finite element model [2] to perform a high-throughput experiment efficiently. The high-throughput experiment (HTE) is the mean to develop new materials efficiently, which is promoted in the Material Genome Initiative (MGI) program. As an essential step, it includes intelligent design and selection of experiments, as well as searching and optimizing a large number of samples under different compositions and processing conditions to accelerate the entire process [3]. After materials processing, the characterization techniques of high throughput are employed to get samples information in a short time. In 1965, Kennedy and his co-workers [4] obtained a phase diagram of alloys to determine the isothermal sections of ternary-alloy on a single substrate containing hundreds of compositions. Hanak [5] proposed a process that included all the elements of HTMD. Moulijn’s group [6] reported parallel reactors that were applied to heterogeneous catalysis in 1980 firstly. At the same time, a Pt-Pd-In ternary catalysts library consisted of 66 combinations was prepared by Senkan et al [7]. In the past two decades, HTEs materials have been rapidly developed and successfully applied in various materials such as metallic, polymers, and inorganic materials. It has indeed facilitated the development of materials research with improved properties.

However, compared with the traditional method, mass of data and many valuable results can be quickly obtained in a shorter time by HTEs, which can directly promote the materials screening or optimize the application of the materials. When faced with a mass of cumulative data, data mining and machine learning, a
powerful artificial-intelligence technique, was employed to deal with it just in time. Machine learning has been proved as a helpful tool in material research. Jiang et al. [8] put forward a new strategy to predict tensile strength for pearlitic steel wires using industrial data combining several machine learning models. Wen et al. [9] designed high entropy alloys with desired property assisted by machine learning. Xue et al. [10] predicted the transformation temperature of shape memory alloys (SMAs) by building up a regression model. Hu et al. [11] adopted the artificial neural network (ANN) to complete a two-way design defined by the prediction of the target properties and designing alloys. By combining genetic algorithm (GA) and back propagation (BP) NN, Reddy et al. [12] established a model based on composition and heat treatment conditions to predict the mechanical properties of low alloy steel.

In the present study, we proposed a screening strategy of processing conditions based on high-throughput experiment equipment, numerical simulation, and machine learning to obtain the optimal condition for hot forging. In our approach, nickel-based superalloy IN718 has been selected as an application case because of its characteristics of high strength, stability, and oxidation resistance at high temperatures [13, 14]. The maximum principal stress on the bulge and average grain size were considered to evaluate the process conditions. We designed high-throughput experiment equipment for hot forging. For the convenience of data preparation, we carry out numerical simulations using finite element software DEFORM 3D. After that, we established two BP NN models by the database built from DEFORM 3D. Based on the searching space consisting of the machine learning predictions, we designed a screening algorithm to guide the search for the best processing conditions, and with that, we get the optimal processing conditions for different forging displacements.

2. Method

2.1. Design of high-throughput equipment

High-throughput equipment that can compress 30 samples at one stroke was designed, shown in figure 1. The equipment includes a top die and a bottom die. The top die has 30 compression bars mounted on it, and each of them is connected with a pressure sensor to record the pressure of each sample in real-time. The bottom die contains five heating rooms. The heat is generated by silicon-carbon rods in the heating rooms and then transferred to sample holders to heat samples. The sample holder is divided into six stages, and the height differences between two adjacent stages are 3 mm, resulting in different forging displacements. Therefore, 30 samples (five temperatures × six forging displacements) can be compressed at once. Besides, different forging speeds and different friction factors can be changed on demand. In this case, experiments with a variety of processing conditions can be carried out.

2.2. Simulation and data collection

A large number of samples should be synthesized and evaluated within a short period to obtain large amounts of data through an experiment. To this end, we performed several simulation experiments using DEFORM 3D. DEFORM 3D is widely used by leading research institutes and manufacturers to simulate material behavior in forming operations. The constitutive equation and microstructure evolution models in DEFORM 3D have enough accuracy and robustness [15–17] and SRINIVASAN et al. [18] have shown that computer models can describe the characteristics of the forging process for IN718. The material of our samples is IN718_6um.
[1650–2200 F (900–1200 C)] from the material library of DEFORM 3D, and the grain model in DEFORM 3D is an Avrami-type equation [15, 16, 19]. The simulation conditions are presented in table 1.

The sample is a cylinder with a size of 10 mm in diameter and 20 mm in height. We initiate the temperature in a range of 900 °C–1100 °C corresponding to five heating rooms, respectively. We assume that the temperatures of the samples, sample holders, and compression bar are the same, so there is no heat transfer...
among them. In other words, we set the heat transfer coefficients between samples and sample holders, samples and compression bars as 0. Meanwhile, the equipment is assumed to be utterly adiabatic so that the heat transfer coefficient between the equipment and the air is set as 0 as well.

As shown in figure 2, a simplified model was imported in DEFORM 3D. 25 samples were forged at one stroke under forging speeds of 1 mm s\(^{-1}\), 2 mm s\(^{-1}\), 10 mm s\(^{-1}\), 20 mm s\(^{-1}\), and 40 mm s\(^{-1}\) and under friction factors of 0.2, 0.4, 0.6, 0.8, and 1. In total, a full factorial experiment with 25 experiments (five forging speeds \(\times\) five friction factors) was performed, as shown in table 2. As a result, 25 samples in one experiment, with 25 experiments, we can get a dataset with a size of 625 (five forging speeds \(\times\) five friction factors \(\times\) five initial temperatures \(\times\) five compression displacements).

After the simulation, we collected the maximum principle stress on the surface of the bulge zone to evaluate the probability of damage, average grain size to evaluate the degree of dynamic recrystallization. In this case, the database consisting of 625 instances with four features (forging speed, friction factor, initial temperature, compression displacement) and two target properties were obtained.

2.3. Machine learning

For maximum principle stress and average grain size, the relationship between them and four features can be expressed as \(Y = f(X_1, X_2, X_3, X_4)\), which is a regression problem. Scikit-learn, a Python framework for data mining and data analysis, can be used to solve it.

Before machine learning, it is necessary to perform data preprocessing. The magnitude difference in the data we collected was enormous. Therefore, the StandardScaler module of Scikit-learn was imported to scale our dataset to have unit norm. Then, several regression algorithms, such as random forest regression (RFR), a regression tree model (CART), support vector regression (SVR), a k-nearest neighbor model (KNN), gradient boosting regressor (GBR), extra tree regression (ETR) and a back-propagation neural network model (BP NN), etc were used for prediction of average grain size and maximum principal stress based on the four features.

Before training, we used the train\_test\_split method in Skit-learn to split our database of 625 instances into 80% training dataset and 20% validation dataset. We used 10-fold cross-validation to select the best performing model in order to avoid overfitting. All the training instances were divided into ten folds for cross-validation and
repeated ten times, which produced different splits in each repetition. GridSearchCV in Scikit-learn was used to adjust parameters. After training, the mean value of root mean square error (mean-RMSE) of the validation dataset was used as the performance metrics. It was calculated in equation (1), where \( \hat{y}_i \) is the value predicted by the machine learning model; \( y_i \) is the true value.

\[
\text{mean}_{-}\text{RMSE} = \frac{1}{10} \sqrt{\frac{1}{m} \sum_{i=1}^{m} (\hat{y}_i - \hat{y}_i)^2}
\]  

(1)

The mean_RMSE values of each algorithm for the validation dataset are shown in figures 3(a) and (b). To test the robustness of our model, we employed a new test dataset of 225 samples that was not in our database to test our model, in which we only selected the best five models, and the result is shown in figures 3(c) and (d). For average grain size, the RFR model is the best performing model in the validation dataset, and the BP NN model is the third-best model. However, in the test dataset, the BP NN model is the best, and the RFR model performs poorly. Therefore, BP NN is selected to be the best algorithm to predict the average grain size. As for the maximum principal stress, BP NN is the best algorithm in both the validation dataset and test dataset, so BP NN is the winner with no doubt. With the two BP NN models we built, the searching space consisting of 1 206 000 processing conditions for IN718 was predicted. A screening algorithm was designed for the optimal processing condition. Our screening strategy for IN718 is schematically shown in figure 4.

Figure 4. A schematic of the screening strategy of the processing conditions for IN718.

Figure 5. The predicted average grain size of the BP NN model as a function of simulated average grain size for (a) all data, (b) the training dataset, (c) the validation dataset, (d) the test dataset. (The dashed line is exactly the diagonal line; the solid red line is the regression fit result of the prediction values and the simulated values).
3. Result and discussion

3.1. Establishment and analysis of two BP NN models

Two BP NN models were trained to predict average grain size and maximum principal stress, respectively. The input is forging speed, forging temperature, forging displacement, and friction factor. The output for the two BP NN models is average grain size and maximum principal stress, respectively.

Figures 5(a)–(d) showed the predicted average grain size of the BP NN model as a function of simulated average grain size for all dataset, training dataset, validation dataset, and test dataset. The data points fall near the diagonal line, indicating that the predicted values of average grain size are consistent with the simulated values well. The solid red line shows the result fitted by predicted values with simulated values. The closer the solid red line is to the diagonal dashed line, the higher the predictive ability of the machine learning model. In this case, it can be observed that the BP NN model for the prediction of average grain size performs very well. Similarly, figures 6(a), (b) shows the predicted maximum principal stress of the BP NN model as a function of simulated maximum principal stress. It showed that the predicted maximum principal stress values are consistent with the simulated values very well.

For test data that is not involved in our database, we further calculated the mean relative error (mean_RE), which is calculated by equation (2).

$$\text{mean_RE} = \frac{1}{n} \sum_{j=1}^{n} \left| \frac{y_j^* - y_j}{y_j} \right|$$

Where $y_j^*$ is the value predicted by machine learning models, $y_j$ is the simulated value, $n$ is the total number of our test dataset, namely 225. The mean_RE for average grain size and the maximum principal stress is 0.49% and 4.4%, respectively, which are within 5%, showing our models have a good predictive performance on unseen data.

3.2. Analysis of processing conditions predicted by two BP NN models

Now that the two BP NN models we built prove to perform well, we analyzed the influence of processing conditions on average grain size and maximum principal stress based on our models.
3.2.1. Effect of processing conditions on average grain size

We performed several predictions under different processing conditions, and the result is shown in Figure 7. We can see from Figure 7 that the predicted average grain size increases with the increase in friction factor and decreases with the increase in forging displacement [20] and forging speed [21, 22]. Significantly, the average grain size decreases with the increase in temperature from 900 °C to 1050 °C first but then increases at temperature >1050 °C. Because of the effect of friction with dies, the top and bottom parts of the samples are the dead zones during deformation, where the dynamic recrystallization can hardly take place [23, 24]. Therefore, a high friction factor leads to bigger grain size. The occurrence of dynamic recrystallization depends on the appropriate temperature. When the temperature grows, the mobility of grain boundaries increases with the rise of forging temperature. Thus, the small dynamic recrystallization grain can grow rapidly and replace previous large grains [25–28]. However, with the further increase in temperature, the grains grow larger and larger, leading to larger average grain size. It can be noted from Row c in Figure 7 that when the forging displacement is less than 6 mm, the average grain size is nearly 100 μm of the original grain size. Hence, the critical displacement for the occurrence of dynamic recrystallization of IN718 is 6 mm–9 mm. The dynamic recrystallization happens quickly when forging displacement is greater than the critical displacement, leading to a drop in the average grain size.
grain size. As for the forging speed, there are mainly two reasons for this result. On the one hand, the alloy under high forging speed has a high work hardening rate and high dislocation density, and thus boosts the nucleation of dynamic recrystallization. On the other hand, the lower forging speed provides a longer time for recrystallization and grain growth [25].

3.2.2. Effect of processing conditions on maximum principal stress

For cylinder samples, the maximum principal stress is concentrated in the middle part, namely the bulge, and is tensile stress. Figure 8 shows that the maximum principal stress increases with the rise of friction factor, forging displacement, and forging speed and declines with the decrease in friction temperature. Due to the influence of the friction on the end surface, the bulge will inevitably increase with the increase in forging displacement, leading to the increasing maximum principal stress. Thus, the bigger friction factor and forging displacement results in greater maximum principal [29], as shown in Row a and Row c. It also can be noted from c1, c2, and c3 that the maximum principal stress difference at large forging displacement is bigger than that at small forging displacement, indicating that the bulge is much more obvious at large forging displacement. As the forging speed increases, the stored deformation energy is too late to release so that the maximum principal stress grows.

Figure 8. Prediction values of maximum principal stress of different processing conditions. Row (a) the predicted maximum principal stress of different friction factors with different temperatures, different forging displacements, different forging speeds; Row (b) the predicted maximum principal stress of different temperatures with different friction factors, different forging displacements, and different forging speed; Row (c) the predicted maximum principal stress of different forging displacement with different friction factors, different temperatures, and different forging speed; Row (d) the predicted maximum principal stress of different forging speed with different friction factors, different temperatures, and different displacements.
However, we can see from Row b that the maximum principal stress declines with the rise of temperature. This is because high temperatures can soften the alloy, making the maximum principal stress smaller [32].

Figure 9. Change trend graph of average grain size and maximum principal stress.

Figure 10. Schematic of the algorithm to find the optimized processing condition.
3.3. Prediction of the optimized processing condition based on our model

From the above results, it can be seen that the prediction results of our model are consistent with the domain knowledge, further confirming the robustness and reliability of our model. So, in the next step, we are going to find out the optimized processing condition based on the machine learning models we just built. As the smaller grain size leads to the material with higher strength and better plasticity and the smaller maximum principal stress results in the smaller tendency of the material to fail, the optimized processing conditions should bring the smallest possible average grain size and the smallest maximum principal stress. However, the changing trend of the grain size and the changing trend of the maximum principal stress are generally opposite and not linear, as shown in figure 9, so it is necessary to find a balance between grain size and maximum principal stress.

To this end, we put forward an algorithm to find out the optimized condition, as shown in figure 10. First, we obtained the predicted values of average grain size and maximum principal stress. Second, we sorted the predicted grain size values from small to large to obtain an ordered array \( A \) with an index. The predicted values of maximum principal stress were processed in the same way, and the ordered array \( B \) of maximum principal stress values with an index was obtained. Third, we take one value \( A_i \) from the array \( A \) and find the corresponding value \( B_i \) in the array \( B \) (\( A_i \) and \( B_i \) are the predicted values under the same processing condition). The summation of indexes of \( A_i \) and \( B_i \) was calculated. Then, the third procedure was repeated until all the \( A_i \)s in array \( A \) was taken. After comparing the sum of all indexes, we can infer that the \( A_i \) and \( B_i \) with the minimum value of \( I_{A_i} + I_{B_i} \) are the optimized grain size and maximum principal stress considering the balance between grain size and maximum principal stress, respectively, and the corresponding optimized processing condition is obtained. As the \( A_i \) and \( B_i \) with the Min(\( I_{A_i} + I_{B_i} \)) mean that both \( A_i \) and \( B_i \) are as close as possible to their respective minimums.

We attempted to screen the optimized processing conditions in the searching space with the above algorithm. During our screening process, the forging speed is set in the range of 1 mm s\(^{-1}\)–40 mm s\(^{-1}\), the friction factor 0.1–1, the forging temperature 900 °C–1100 °C, the forging displacement 1 mm–15 mm, forming the searching space of 1 206 000. The optimized processing conditions for five different forging displacements are obtained and listed in table 3.

It can be inferred from table 3 that the friction force should be as small as possible, so we represent the variation of the sum \( I_{A_i} + I_{B_i} \) with forging temperature and forging speed under the friction factor of 0.1, as shown in figure 11. The optimal conditions for different forging displacements are marked. It can be seen from
figure 11 that the blue areas with smaller values of $I_{IA} + I_{IB}$ indicate the relatively better processing conditions. With the increase in the forging displacement, the blue area becomes more concentrated in the area with lower temperatures and lower forging speed. The Bulge zone is more prone to cracking at large forging displacement, which can be relieved by appropriately increasing the deformation temperature and reducing the deformation speed, while also ensuring that the grain size is appropriate.

4. Conclusions

In summary, we proposed a screening strategy of processing conditions based on high-throughput experiment equipment, numerical simulation, and machine learning to obtain the optimal process condition for hot forging. High-throughput experiment equipment of hot forging for 30 samples was designed. With IN718 as an example, we performed several numerical simulations of the forging process on the equipment and formed a database of 625 examples with four features and two target properties. Based on the database, two BP NN models were trained to construct the searching space of 1 206 000 and with a screening algorithm comprehensively considering the average grain size and the maximum principal stress in the bulge zone, we obtained the optimal processing conditions for different forging displacements. Compared with the traditional high-cost and time-consuming trial-and-error methods, the method used in this paper to optimize the processing technology has great advantages. This method could also be applied to other optimizations of the forging process, which is beneficial to pre-screening for material design and process optimization.

Acknowledgments

This work was financially supported by the National Key Research and Development Program of China (2017YFB0701801, 2017YFB0701803).

ORCID iDs

Zhiren Sun https://orcid.org/0000-0001-9340-1978

References

[1] Juillet C, Oudriu A, Balmain J, Feaugas X and Pedraza F 2018 Characterization and oxidation resistance of additive manufactured and forged IN718 Ni-based superalloys Corros. Sci. 142 266–76
[2] Sheppard T and Duan X 2003 Modelling of static recrystallisation by the combination of empirical models with the finite element method J. Mater. Sci. 38 1747–54
[3] Liu Y, Hu Z, Suo Z, Hu L, Feng L, Gong X, Liu Y and Zhang J 2019 High-throughput experiments facilitate materials innovation: a review Science China-Technological Sciences 62 521–45
[4] Kennedy K, Stefansky T, Davy G, Zackay V F and Parker E R 1965 Rapid method for determining ternary-alloy phase diagrams J. Appl. Phys. 36 3808–10
[5] Hanak J 1970 The ‘multiple-sample concept’ in materials research: synthesis, compositional analysis and testing of entire multicomponent systems J. Mater. Sci. 5 964–71
[6] Thomas R, Moulijn J A, De Beer V H J and Medema J 1980 Structure/metathesis activity relations of silica supported molybdenum and tungsten oxide J. Mol. Catal. 8 161–74
[7] Senkan S, Krantz K, Ozturk S, Zengin V and Onal I 1999 High-throughput testing of heterogeneous catalyst libraries using array microreactors and mass spectrometry Angew. Chem. Int. Ed. 38 2794–9
[8] Jiang X et al 2020 A strategy combining machine learning and multiscale calculation to predict tensile strength for pearlitic steel wires with industrial data Scr. Mater. 186 272–7
[9] Wen C, Zhang Y, Wang C, Xue D, Bai Y, Antonov S, Dai L, Lookman T and Su Y 2019 Machine learning assisted design of high entropy alloys with desired property Acta Mater. 170 109–17
[10] Xue D, Xue D, Yuan R, Zhou Y, Balachandran P V, Ding X, Sun J and Lookman T 2017 An informatics approach to transformation temperatures of NiTi-based shape memory alloys Acta Mater. 125 532–41
[11] Hu X B, Wang J C, Wang Y Y, Li J, Wang Z I, Dang Y Y and Gu Y F 2018 Two-way design of alloys for advanced ultra-supercritical plants based on machine learning Comput. Mater. Sci. 155 331–9
[12] Reddy N S, Krishnaiah J, Young H B and Lee J S 2015 Design of medium carbon steels by computational intelligence techniques Comput. Mater. Sci. 101 120–6
[13] Zhao Y, Guo Q, Ma Z and Yu L 2020 Comparative study on the microstructure evolution of selective laser melted and wrought IN718 superalloy during subsequent heat treatment process and its effect on mechanical properties Materials Science & Engineering A 791 1–8
[14] Du J H, Lv X D, Dong J X, Sun W R, Bi Z N, Zhao G P, Deng Q, Cui C Y, Ma H P and Zhang B J 2019 Research progress of wrought superalloys in China Acta Metall. Sinica 55 1115–32
[15] Shen G, Semiatin S L and Shippur R 1995 Modeling microstructural development during the forging of Waspaloy Metallurgical and Materials Transactions A 26 1795–803
[16] Devadas C, Samarasereka I V and Hawbolt E B 1991 The thermal and metallurgical state of steel strip during hot rolling: III. Microstructural evolution Metall. Trans. A 22 335–49
Arrazola P J, Kortabarria A, Madariaga A, Esnaola J A, Fernandez E, Cappellini C, Ulutan D and Özel T 2014 On the machining induced residual stresses in IN718 nickel-based alloy: experiments and predictions with finite element simulation Simul. Modell. Pract. Theory 41 87–103

Srinivasan R, Ramnarayan V, Deshpande U, Jain V and Weiss I 1993 Computer simulation of the forging of fine grain IN-718 alloy Metall. Trans. A 24 2061–9

Na Y-S, Yeom J-T, Park N-K and Lee J-Y 2003 Simulation of microstructures for alloy 718 blade forging using 3D FEM simulator J. Mater. Process. Technol. 141 337–42

Zhang J M, Gao Z Y, Zhuang J Y and Zhong Z Y 1999 Mathematical modeling of the hot-deformation behavior of superalloy IN718 Metallurgical and Materials Transactions A 30 2701–12

Xie G-L, He A, Zhang H-L, Wang G-Q and Wang X-T 2016 A physically based dynamic recrystallization model considering orientation effects for a nitrogen alloyed ultralow carbon stainless steel during hot forging Journal of Iron and Steel Research(International) 23 364–71

Zhou L X and Baker T N 1995 Effects on dynamic and metadynamic recrystallization on microstructures of wrought IN-718 due to hot deformation Materials Science and Engineering: A 196 89–95

Malayappan S and Narayanasamy R 2004 An experimental analysis of upset forging of aluminium cylindrical billets considering the dissimilar frictional conditions at flat die surfaces The International Journal of Advanced Manufacturing Technology 23 636–43

Zhang H Y, Zhang S H, Li Z X and Cheng M 2010 Hot die forging process optimization of superalloy IN718 turbine disc using processing map and finite element method Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture 224 103–10

Chen M-S, Lin Y C, Li K-K and Zhou Y 2016 A new method to establish dynamic recrystallization kinetics model of a typical solution-treated Ni-based superalloy Comput. Mater. Sci. 122 150–8

Bontcheva N and Petzov G 2003 Microstructure evolution during metal forming processes Comput. Mater. Sci. 28 563–73

Medeiros S C, Prasad Y V R K, Frazier W G and Srinivasan R 2000 Microstructural modeling of metadynamic recrystallization in hot working of IN718 superalloy Materials Science and Engineering: A 293 89–95

Park N K, Kim I S, Na Y S and Yeom J T 2001 Hot forging of a nickel-base superalloy J. Mater. Process. Technol. 111 98–102

Cai S-P and Wang Z-J 2020 An analysis for three-dimensional upset forging of elliptical disks and rings based on the upper-bound method Int. J. Mech. Sci. 183 105835

Huang S-H, Shu D-Y, Hu C-K and Zhu S-F 2016 Effect of strain rate and deformation temperature on strain hardening and softening behavior of pure copper Transactions of Nonferrous Metals Society of China 26 1044–54

Zhou L X and Baker T N 1994 Effects of strain rate and temperature on deformation behaviour of IN 718 during high temperature deformation Materials Science and Engineering: A 177 2701–12

Cha D J, Kim D K, Cho J R and Bae W B 2011 Hot shape forging of gas turbine disk using microstructure prediction and finite element analysis Int. J. Precis. Eng. Manuf. 12 331–6