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Hybrid intelligent parameter estimation based on grey case-based reasoning for laminar cooling process

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ABSTRACT

In this paper, a hybrid intelligent parameter estimation algorithm is proposed for predicting the strip temperature during laminar cooling process. The algorithm combines a hybrid genetic algorithm (HGA) with grey case-based reasoning (GCBR) in order to improve the precision of the strip temperature prediction. In this context, the hybrid genetic algorithm is formed by combining the genetic algorithm with an annealing and a local multidimensional search algorithm based on deterministic inverse parabolic interpolation. Firstly, the weight vectors of retrieval features in case-based reasoning are optimised using hybrid genetic algorithm in offline mode, and then they are used in grey case-based reasoning to accurately estimate the model parameters online. The hybrid intelligent parameter estimation algorithm is validated using a set of operational data gathered from a hot-rolled strip laminar cooling process in a steel plant. Experiment results show the effectiveness of the proposed method in improving the precision of the strip temperature prediction. The proposed method can be used in real-time temperature control of hot-rolled strip and has potential for parameter estimation of different types of cooling process.

1. Introduction

In steel manufacturing industry, the hot-rolled strip laminar cooling (HSLC) process is used to cool a strip from a finishing rolling temperature of roughly 820–920 °C down to a coiling temperature of 400–680 °C. Strips enter laminar cooling section after the finishing mill, then are cooled in the water cooling section, and finally are coiled by coiler. When the strip is cooled down on the run-out table, the mechanical properties of the corresponding strip are determined by the cooling curve (Tang et al., 2007; Sha et al., 2007). Therefore the highly flexible and precise control of the cooling curve and coiling temperature in the cooling section is extremely important for the product quality.

However, since it is difficult to measure the strip temperature continuously while in the cooling section, establishing a dynamic parametric model to estimate the strip temperature plays an important role in controlling the hot-rolled strip temperature. A fixed-parameter model can represent a certain product type (i.e. grade). However, in strip manufacturing process, many different grades need to be produced which necessitates using a parameter-varying dynamic model to predict the temperature. Each grade is identified using a number of different process settings (e.g. moving speed, strip temperature, etc.). Then, in order to manufacture the required grade, the cooling water distribution is adjusted, so that the desired product attributes are obtained. Consequently, rapidly changing operating conditions of cooling process lead to the instability of heat transfer characteristics. The model parameters represent the thermal characteristics of the cooling process, such as heat transfer coefficient which is influenced by many variables including ambient temperature, hardness grade of strip, strip thickness, temperature of cooling water, strip moving speed, strip temperature, and the distribution of cooling water. Since the resulting dynamic model parameters, e.g. the heat transfer coefficient are nonlinear and time varying, the mathematical model derivation is extremely difficult. Furthermore, traditional estimation techniques fail to estimate nonlinear parameters accurately due to the lack of prior process knowledge. In order to overcome these difficulties, an estimation technique based on case-based reasoning (CBR) has been considered in Tan and Chai (2005). However, the authors have considered to determine the weights of CBR features based on operator's expert experience, which incorporates significant uncertainties from one operator to another, and as a result, to inaccurate estimation of the parameters. In this paper, a new algorithm hybrid genetic algorithm (HGA) is developed to optimise the weights of CBR features.

1.1. CBR background

The CBR is formed of concepts and techniques which relate to knowledge representation, reasoning, and learning from experience (Aamodt and Plaza, 1994; Wettschereck and Aha, 1995; Bonzano et al., 1997; Jarmulak et al., 2000; Coyle and Cunningham, 2004; Xiong and Funk, 2006; Ahn et al., 2006; Sun and Li, 2009;

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Xiong, 2011). Perhaps the most significant advantage of CBR is similarity of its prediction approach to that of human reasoning system which makes predictive processes and results easily understandable to industrial users. It is known that human beings always search their memories to find similar experiences when they encounter a new problem. The human reasoning system can learn over time, reason in domains with incomplete or non-well-defined concepts, and provide means for explanation. The CBR is a well established methodology with broad applications such as medical science (Ahn and Kim, 2009), finance (Li and Ho, 2009), electronics (Chang et al., 2008), chemical engineering for quality design (Suh et al., 1998), intelligent Web-based sales service (Watson and Gardingen, 1999; Wilke et al., 1998), building and mechanical design (Nikolaychuk and Yurin, 2008; Rivard and Fenves, 2000; Mileman et al., 2002), material science (Amen and Vomacka, 2001; Mejasson et al., 2001), complex fault finding and troubleshooting (Aha et al., 1999) as well as planning and real-time scheduling tasks (Cunningham et al., 1997; Coello and dos Santos, 1999).

Generally, the process of CBR consists of four steps: retrieve, reuse, revise, and retain (Kolodner, 1993). To find a solution to a new problem case, it is first necessary to search similar cases. After assessing the similarity of the retrieved cases, the solution is reused. Alternatively, new knowledge is used to establish a new case, through the adaptation process. The performance of CBR relies on the composition of a case base, similarity assessment, and a case adaptation method, in which similarity assessment plays an important role (Aamodt and Plaza, 1994). Many CBR-based systems represent cases using features and employ a similarity function to measure the similarities between new and historical cases (Shin and Han, 1999). The approach commonly used to assess similarity is the distance function including the Euclidean distance (Cheng et al., 2008; Elhadi, 2000; Kwong and Tam, 2002) and the Manhattan distance (Bryant, 1997; Yu and Liu, 2006). Chiu et al. (2003) proposed GA-based feature weighting together with number of nonlinear similarity functions based on standard the Euclidean distance metric.

So far the main stream of the works involving similarity models has been focused on feature weighting (Kohavi et al., 1997; Wettschereck and Aha, 1995). Features are assigned with different weights in accordance with their importance and the global similarity metric is defined as a weighted sum of the local matching values in single attributes (Xiong, 2011). Different approaches have been proposed for estimating such weights automatically. Feature weights are modified by incremental learning according to success/failure feedback of retrieval results (Bonzano et al., 1997; Ricci and Avesani, 1995). Probability-based techniques are used to assign weight values to features utilising conditional probabilities of classes and the probability of ranking principle (Creecy et al., 1992; Cercone et al., 1999). For weight adaptation, the case-ranking information is used as the similarity degree of case retrieval (Branting, 2001; Coyle and Cunningham, 2004; Stahl and Gabel, 2003). An accuracy improvement method has been proposed representing an approach for adapting the set of weights (Jarmulak et al., 2000; Ahn et al., 2006). Xiong (2011) has also proposed a new method to similarity assessment based on fuzzy rule-based reasoning and advocate that the set of fuzzy rules for similarity assessment can be learned from the case base using genetic algorithms.

1.2. Hybrid genetic algorithm for optimisation

GA has been widely applied to control systems and is one of the most powerful Artificial Intelligence (AI) techniques (Bedwani and Ismail, 2001). Compared with gradient-based search algorithms, GA is very suitable for optimisation problems with several local minima. It is also effective if the search space is either (partially) non-differentiable or discontinuous (Kargupta and Smith, 1991; Kristinsson and Dumont, 1992). The GA techniques have been applied to identify linear and non-linear systems by many researchers. For instance, Hossain et al. (1995) have used GA for parameter estimation of a flexible beam to design a vibration controller where a first order central finite difference (FD) method was used to study the behaviour of the beam.

The main disadvantages of GA, however, are the slow convergence to global optimum and the premature convergence. In order to overcome the convergence speed problem, this paper employs a truncation-based selection algorithm (Tavakolpour et al., 2010). The selection strategy involves replacing the weakest member of the present generation with the strongest member of the previous generation. This strategy improves the performance of the GA by ensuring monotonic improvement in the best fitness value of each generation. The second problem, i.e. premature convergence, is caused by the loss of diversity in population, especially when the search is continued for several generations (Gudla and Ganguli, 2005). Hence, an annealing algorithm is employed to overcome the drawback in the way that each member of a new population is obtained by the self-recognition crossover and mutation operators and then is determined whether to enter the next population according to the Metropolis criteria in annealing algorithm.

1.3. Objectives and contributions

The objective of this paper is to accurately estimate the cooling temperature model parameters so that the accuracy of predicting temperature distribution and cooling temperature of strip in the laminar cooling process are improved. For this purpose, a hybrid intelligent parameter estimation algorithm formed by a hybrid genetic algorithm and grey case-based reasoning is proposed. The HGA is used to optimise the weights of retrieval features in case-based reasoning which is considered an advantage over the existing methods in which the weight values are determined by expert experience. The weight vector is then used by grey case-based reasoning to accurately estimate the model parameters online. The proposed method is validated using a set of operational data gathered from hot-rolled strip laminar cooling process. Experiment results show significant precision improvement in the prediction of strip temperature in the laminar cooling process.

The rest of this paper is organised as follows. In Section 2, the laminar cooling process is presented, and then the problem of parameter estimation of the thermodynamic model is discussed. In Section 3, a detailed description of the proposed hybrid intelligent parameter estimation method is presented. Section 4 presents the implementation and results of the proposed method. Concluding remarks are made in Section 5.

2. Process description and related work

2.1. Process description

The schematic diagram of a laminar cooling process is illustrated in Fig. 1. Strips enter cooling section after the finishing mill at finishing rolling temperature of 820–920 °C. After being cooled in the water cooling section, the strips are coiled at coiling temperature of 400–680 °C. Strips are 200–1100 m in length and 6.30–13.20 mm in thickness. There are 90 top headers and 90 bottom headers on the run-out table. The top headers that are of U-type are used for laminar cooling and the bottom headers that are of straight type are used for low pressure spraying. These cooling water headers are divided into 12 groups. The first nine groups are considered as the main cooling section and the last three groups are the fine cooling section. The corresponding thermodynamic model is presented in Appendix A.