Advanced Engineering Informatics 30 (2016) 553–563

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Data-driven train operation models based on data mining and driving experience for the diesel-electric locomotive

Chun-Yang Zhang [a], Dewang Chen [a,*], Jiateng Yin [b], Long Chen [c]

[a] College of Mathematics and Computer Science, Fuzhou University, Fuzhou, China
[b] State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China
[c] Faculty of Science and Technology, University of Macau, Macau

ARTICLE INFO

Article history:
Received 6 December 2015
Received in revised form 20 June 2016
Accepted 20 July 2016

Keywords:
Machine learning
Ensemble learning
Data-driven train operation model
Automatic train operation
Manual driving

ABSTRACT

Traditional control methods in automatic train operation (ATO) models have some disadvantages, such as high energy consumption and low riding comfort. To alleviate these shortcomings of the ATO models, this paper presents three data-driven train operation (DTO) models from a new perspective that combines data mining methods with expert knowledge, since the manual driving by experienced drivers can achieve better performance than ATO model in some degree. Based on the experts knowledge that are summarized from experienced train drivers, three DTO models are developed by employing K-nearest neighbor (KNN) and ensemble learning methods, i.e., Bagging-CART (B-CART) and Adaboost.M1-CART (A-CART), into experts systems for train operation. Furthermore, the DTO models are improved via a heuristic train parking algorithm (HPA) to ensure the parking accuracy. With the field data in Chinese Dalian Rapid Rail Line 3 (DRRL3), the effectiveness of the DTO models are evaluated on a simulation platform, and the performance of the proposed DTO models are compared with both ATO and manual driving strategies. The results indicate that the developed DTO models obtain all the merits of the ATO models and the manual driving. That is, they are better than the ATO models in energy consumption and riding comfort, and also outperform the manual driving in stopping accuracy and punctuality. Additionally, the robustness of the proposed model is verified by a number of experiments with some steep gradients and complex speed limits.

1. Introduction

In recent years, urban rail transit has been developed rapidly due to its superiorities of high-speed, punctuality and safety in public transportation systems [1]. Most large cities all over the world are expanding their subway systems to relieve the pressure of public transportation. The efficiency of a subway system is largely determined by the train driving strategies. In most new established subway systems, automatic train operation (ATO) systems, that control a train to accelerate, coast or brake automatically, have replaced the manual driving methods [2]. The ATO models has been developed for many years. For example, fuzzy control and predictive fuzzy control were developed to overcome the complexity of train control model [3]. Chang proposed a genetic algorithm (GA) to optimize train movements using appropriate coast control [4]. Hou proposed iterative learning control (ILC) theory to make the train tracking the given guidance trajectory more precisely by iterative learning process [5]. To overcome the traction/braking saturation of train dynamic model, Song [6,7] designed a computationally inexpensive tracking control method in which a single-coordinate dynamic model that reflected in-train forces was derived.

It is known that subway train operation system requires multiple objectives, including operation safety, train parking error, energy consumption, and passenger comfort, etc [8]. The train control can be regarded as regression problem with several variables. The simple linear models like auto-regression models are very fast but produce poor performance in punctuality, safety, passage comfort, and energy efficiency. The neural network based nonlinear regression models, such as SVM, ANFIS, and current popular deep learning models, are too complex against the real-time response [9,10]. Therefore, this paper develop a empirical model to find a good balance between efficiency and complexity. In other words, they are more practical for the train control. In addition, most current ATO models are developed to track a target speed curve as precisely as possible. Thus, they need to frequently adjust

* Corresponding author.
E-mail addresses: zhangcyfst@sina.com (C.-Y. Zhang), dwchen@fzu.edu.cn (D. Chen), jiatyin@bjtu.edu.cn (J. Yin), longchen@umac.mo (L. Chen).

http://dx.doi.org/10.1016/j.aei.2016.07.004
1474-0346/

the control output, which will reduce the riding comfort and increase energy consumption [11–13].

A large amount of train operation data are recorded everyday by the ATO systems and manual driving. For research studies, the field data from Dalian Rapid Rail Line 3 (DRRL3) was collected. From statistical analysis on the practical data, one interesting fact is discovered that the manual driving by experienced drivers is better than the automatic driving in energy consumption and riding comfort [14]. Some preliminary works by using data mining techniques have been done to design some human driving rules [15,16]. On the foundation of the preliminary works, the contributions of this paper can be summarized as follows: (1) Combining the driving experiences, the automatic train operation, data mining techniques, and a heuristic train parking algorithm (HPA) together, three new DTO models based on KNN, B-CART and A-CART, are proposed; (2) all the three DTO models are trained and evaluated with real-world data sets from DRRL3 to evaluate their effectiveness; (3) the robust analysis is developed to verify the performance of the models in different kinds of extreme situations. In brief, this work aims to establish effective data-driven train operation (DTO) models from a new point of data mining to improve the overall performances and robustness of subway train operations [17].

The rest of the paper is organized as follows. Section 2 describes the problem of train operations for the diesel-electric locomotives. In Section 3, the domain driving experiences are summarized, and three models, i.e., DTO_K, DTO_B and DTO_A are developed based on KNN, B-CART and A-CART, respectively. In Section 4, a heuristic parking algorithm (HPA) will be proposed to improve the parking accuracy. In Section 5, a number of criteria are presented to evaluate the performance of the three models. In Section 6, the models are evaluated and analyzed in detail by using the field operation data in DRRL3. Furthermore, the robustness of the DTO models are verified with steep gradient and complex speed limits. Finally, a conclusion is arrange in Section 7.

2. Problem statement

In general, a train control model can be expressed as

$$Mu = M \times \frac{dv}{dt} - f_r(v) - f_g(s), \tag{1}$$

$$\frac{ds}{dt} = v, v < v_l, \tag{2}$$

where M, v and s are the mass, velocity and position of a train, u represents the output of the train controller and v_l represents the speed limit, which is the speed that a train cannot exceed. In addition, $f_r(v) = \alpha v^2 + \beta v + \gamma$ describes the resistances produced by friction. $f_g(s) = Mg\sin(r)$ represents the resistances aroused by gradients, and r is the slope angle [18]. Then, Eqs. (1) and (2) can be written as

$$\begin{aligned} u &= \frac{dv}{dt} - f_r(v)/M - f_g(r,s)/M \\ &= f(v,s,t,r,v_l). \end{aligned} \tag{3}$$

The nonlinear property and time delay in a train accelerating/braking system have been studied in [19] as

$$\dot{u}_a(t) = -\eta \frac{1}{t_p} u_a(t) + \frac{1}{t_p} u(t - t_d), \tag{4}$$

where t_d and t_p represent the time delay and time constant of train accelerating/braking model, respectively. However, all the aforementioned parameters are extremely difficult to precisely obtain in practice, including $\alpha, \beta, \gamma, t_d, t_p$ and M. Train mass M may vary between stations due to on-off passengers, and α, β and γ are related to many factors, e.g., the line conditions. As a result, it is very intractable to design a precise controller for the train, since the parameters of the model are dynamic and uncertain. From Eq. (3), it is easy to see that the variables are the current speed, position, running time, gradients and speed limits. To employ the data mining approach, it is reasonable to first record all data pairs in daily operations of DRRL3 in the form of

$$D = \begin{pmatrix} x_1^1 & x_1^2 & \cdots & x_1^n \\ x_2^1 & x_2^2 & \cdots & x_2^n \\ \vdots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^n \\ \vdots & \vdots & \ddots & \vdots \\ x_5^1 & x_5^2 & \cdots & x_5^n \\ y^1 & y^2 & \cdots & y^n \end{pmatrix}, \tag{5}$$

where n represents the amount of data sets, x_i and y represent the inputs and outputs. As shown in Fig. 1, the trains used in DRRL3 are a type of diesel-electric locomotives [18]. It means that the output of controller u can take only a finite number of pre-determined values subject to $-1 \leqslant u \leq 1$. For example, the set of outputs for the locomotives in DRRL3 is expressed as

$$u \in \begin{pmatrix} -0.8 & -0.6 & -0.5 & -0.4 & -0.3 & -0.2 & -0.1 \\ 0 & & & & & & \\ 0.25 & 0.5 & 0.75 & 1 & & & \end{pmatrix}. \tag{6}$$

In the running process of a train, there are three train operation modes, i.e. traction mode, braking mode and coasting mode, which correspond to that u is a positive value, a negative value or, u equals zero. The output u of the controller for a diesel-electric locomotive is an element of a set of predefined finite discrete numbers. In other words, the positive numbers mean traction, negative numbers refer to braking, and their absolute values refer to the degree of traction or braking. Therefore, with these field data, it is safe to treat train operations as a classification problem, and the DTO modeling will be presented in the following section.

3. DTO modeling

3.1. DTO framework

As shown in Fig. 2, the framework of DTO models is motivated by achieving a data-driven control system. The inputs consist of an expert knowledge database, an offline database and an online database. The driving experiences, data mining algorithms and a heuristic parking algorithm are developed in the second column. Combined with K-nearest neighbor, Bagging-CART and Adaboost. M1-CART, three DTO models, i.e. DTO_k, DTO_B and DTO_A, are proposed, respectively. The DTO models are developed to achieve the following advantages:

- The DTO models do not require the precise parameter learning in ATO models.
- The DTO models do not need to approximate the target speed curve.
- The DTO models only use offline data to train and test by data mining techniques, and can also operate a train with online data.
- The DTO models show better performance in the multiple objectives.