IOP Conf. Series: Materials Science and Engineering **452** (2018) 032055 doi:10.1088/1757-899X/452/3/032055

Train Energy-Saving Scheme Optimized On Case Intelligence with Synthesis-Reasoning Technology in Urban Rail Transit

Jianyang Li[1, a], Hongseng Wu[2, b], Benkun Zhu[2]

[1]School of Electrical Engineering and Automation Zhenjiang Institute of Technology Zhenjiang, China
[2]School of Computer and Information Engineering Hefei University of Technology Hefei, China

[a]lijianyang@sina.com, [b]Hongseng1 @sina.com

Abstract. Train energy consumption in URT has been attracted much greater concerns for it becomes more serious with the large scale operation and expansion of operation network. One of the important ways for energy-saving propulsion is to find the energy-efficient train speed curve, which is a complicated CSP (constraint satisfaction problem) with uncertainty, and cannot be solved effectively with such inconsistent constrains. The case intelligent based on CBR (case-based reasoning) is proposed in this paper for its problem-solving ability, for which the domain expertise is rich while rule knowledge deficient, to construct a flexible system integrated with efficient machine learning components and acquire the train operation preferences from the former stored cases. The experiments testing on the spot indicates that the system performs well in synthesis-reasoning, which can conquer the complexity and uncertainty of real problem from both RBR (Rule-based reasoning) and CBR, to minimize the energy consumption for train traction with punctuality and safety demands.

1. Introduction

The problem of energy consumption in URT becomes more serious along with the large scale operation and expansion of operation network, and takes terrible proportion of energy consumption. Through a decade development URT has become the mainstream of public transport in most of China large cities for green transportation, and more than forty URT lines have been built in Beijing, Shanghai, Guangzhou and other cities with a mileage of 5,000 kilometers. Many more electric energies are demanding for URT operation, causing most of their tickets income paid for the electricity bills. Resulting in high budget deficit from URT operating losses, it was absolutely essential way to reduce the energy consumption in each URT, which has caused the most prominent problem from daily operations.

Energy-saving train operation can be formulated as a problem of optimal control, which aims to calculate the optimal reference speed profile compromising on all kinds of control parameters, and a large number of studies have been carried out from both analytical and numerical methods since1960s. [1] Considers the problem of determining an optimal driving strategy in control with a generalized equation of motion. [2] Uses the Pontryagin principle to find necessary conditions and shows these conditions yield key equations. [3] Uses the Kuhn–Tucker equations to find key equations that determine the optimal switching times. [4] Obtains the optimal solution for the operation of a train on a variable grade profile subject to speed restrictions.

Due to the complexity of the above analytical methods, many researches have constructed large of simulating methods on energy-saving, such as dynamic programming, genetic algorithm, fuzzy control, artificial neural networks, quadratic sequence planning, ant colony optimization, etc. [5-8]. Singaporean scholar uses genetic algorithms to generate inertial control tables to optimize the operational control of their MRT system [9, 10], Australia SCG developed their online operation guidance system METROMISER, which can calculate the train operation process to optimize driving in real-time [11, 12].

Researches also shows that the factors affecting train energy consumption mainly include traction and braking performance, train weights and speed, metro line parameters, signaling blocking mode and train operation mode, which are difficult to obtain the optimal solution due to the complexity of the train operating environment along with real-time passenger flow changing. So far, the precise calculation of traction and energy consumption is still a difficult task, causing researches either simplify the calculating model, or assume running in specific conditions omitting certain constrains.

From the view of recognition, problem-solving can be used by the traditional Rule-based reasoning (RBR), just like what we have described the both researches have done, that is a kind abstract thinking of human merely. Experts in the decision-making really uses more imaginative thinking - Case-based reasoning (CBR)- to perform analogy model for creative reasoning [13], which is a kind of inferential study strategy allowing people to process their reasoning course for new problem-solving wherever they have similar characters. Case-intelligent system based on CBR performs well in weak area full of domain expertise but lack knowledge like fault diagnosis, help-desk support, online e-commerce and online decision guides, etc. [14]. As many researches have bothered by the real complex constrains on the URT train optimized operation, which are more complicated and with inconstant impact-factors, here we present the case-intelligent learning to solve such problems.

2. Synthesis- Reasoning modeling

2.1. Cases Collection

As we know one URT train is running from the same route station A to B many times a day, about which its VOBC (Vehicle on-board Computer) records these propulsion parameters, large amounts of propulsion data are stored for long time running; in the meantime this kind of URT trains in the same line are also stored huge propulsion data. The big data of the URT train operation implicitly gives many empirical knowledge, which are effective to optimized operation but to be difficultly obtained with brief knowledge – the running ‘rule’ for the optimal solution accounting for the complexity of the train operating environment.

People often use the analogy reasoning models and assumptions to study new concepts and find new knowledge like this:

Object X has attributes a, b, c, d, e.

Object B has attributes a, b, c, e.

It suggests us that B may have similar attributes d. The so-called mapping analog is to compare two similar things, searching for their similar relations at a certain level and as a reason to map the problem space, through which solves the new issues by appropriate knowledge transformation, and the matching methods can be composed by partial similar attributes, partial matching feature, or even by interpretable matching. Naturally we can define URT train propulsion cases learning as follows:

1) Suppose a URT train serials run from station A to station B, each VOBC control the train routing and record its real speed curve, S1,S2,…,Sn, from which we can find the best speed curve Si with the least energy consumption.

2) Another URT train X running from station A to station B, can reuse the best speed curve Si by analogy mapping and case adaptation to perform CBR process, for they have the most similar running constrains.

3) Case library collects both kind of running big-data from the same route AB, the one propulsion cases is drilling from itself, the others come from the same kind of train, for they have the most similar dynamic presentation under the same signal system.

4) case library can also collects propulsion cases from the similar kinds of train and similar speed curve under different route by transfer learning, either from the different kinds of train ideally but not mentioned in this paper just now, for the learning is really so time-consuming that cannot meet the real-time ATO (Automatic Train Operation) demands.

2.2. System Modeling

In general, CBR system implements four processes such as Retrieve, Reuse, Revise, and Retain, well known as the 4R. According to the problem (target case) space, it obtains the similar former cases (base case) from the source case library, to deal with the similar circumstances, appropriately adapting to new situation for the new problem-solving. The former cases can also be used to evaluate the new issues, new statues and programs of problem-solving, and prevent the potential errors in the future.

Vehicle data base stores primary train parameters, such as Maximum Train Acceleration/Maximum Train Service Brake Rate/ Train Length /Max wheel diameter /Min wheel diameter Normal brake average decelerate, etc. Line data base stores such Metro Line parameters involving train operations like types of switches, state and position/ Permanent Speed Limit / Proximity plates / Axle detection point / Minimum radius of plane curves of the guideway /Maximum gradient at vertical sections of different guideways/ Wayside Radio Units and Access Points, etc.

As fig 1 described, analogy in the minds of human beings plays a very important role, for which people's knowledge are gradually built up. The new problem are mapping and compared with the original knowledge which have been carried out of case library, and can reason from similar knowledge transfer (synthesis reasoning), just like what we have been searching for the running rule of the optimal solution. In order to improve the CBR system retrieval efficiency with our synthesis reasoning process, the best way is to integrate three organizational strategies, which performs well in our system described in paper [15].

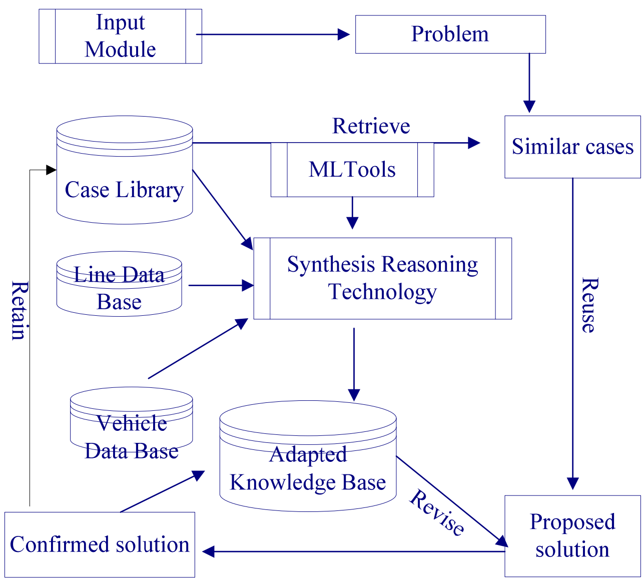

Figure 1. The improved system model

2.3. Synthesis Reasoning Technology

The problem of optimized URT energy-saving operation is a extremely complex CSP, which consists of a set of variables V = {V1, ..., Vn}, corresponding to the domain of values r={ r1, r2, ... rm } of each variable, and a set of constraints C = {C1, ..., Ck}. As many researches have done, only when we should search an assignment for each variable to fit for all constraints, can it get the optimized energy-saving operation. But each constraint describes a legal combination of a subset of variables with a particular fickle value, which is changeable with URT running environment. For example, monitoring the train real speed is the most important to train safety protection, when the train spin/ slide, or wheel diameter attrition causing by the steel surface humidity, the changing process can't be a steady with a definite value for they must vary from a range. That's why many researches must simplify the CSP, and intelligent simulation performs well for such problem-solving.

The traditional view of reasoning is a process by its causality (expressed as a 'rule'- the reasoning chain, RBR) to derive the conclusion. But for the real URT train operation, the optimized problem is about uncertain and incomplete, for which traditional knowledge processing RBR can only work well on the basis of sufficient complete and clear understanding, once the information is missing or blurred, its reasoning ability will be drastically reduced. Therefore, the system integrated with RBR and CBR is expected to construct our case-intelligent system, to give full play to their advantages, for the naive CBR method does not guarantee the good performance of the system efficiency in the real URT operation, which needs to be cooperated with RBR where the rule is acquired by machine learning (ML) technology. There are many methods to combine CBR and RBR for problem-solving in our system, for they have excellent flexibility.

3. Experiments and Explanation

3.1. Experimental Planning

To meet the train safety demands is the chief task to process any test on the spot, where the URT train operating modes are divided into two general classes: ATC modes - the train is controlled by the ATC system, and manual modes - the train is under the control of a driver. Considering many kinds of trains running all over the world taken from different signaling systems, their inconsistent Abbreviations and Acronyms may confuse us, so we briefly take a look.

When Mode Selection Switch is in the ATO position, VOBC enters the ATO mode and controls the vehicle without driver intervention; CM position (Cab Manual mode) or other ATPM (ATP Manual mode) has ATP and IATP protection mode, the train functions of acceleration, coasting, deceleration, stopping, and door opening are under the direct manual control of the Train Operator and are supervised by the ATP system with the driving information shown on the TOD, so our experiments are taken on the spot with CM or ATPM mode.

our experimental CBR software system is designed in components for easily integrated with many ML tools, such as RS and RBF in our experiments. Due to the train RAMS requirements, our software cannot be directly inserted into VOBC system software, so the train energy consume and traction force calculating can be only reflected with the position of driver operation handle instead. A digital electricity meter is recording the real-time energy consume with a period of 3 seconds, so it can be added up for the interval real energy consume to demonstrate our testing results. Thus, each case has such attributes: Case={start point, end point, start point speed, end point speed, line conditions, passenger flows, Traction Force, etc. }. Summarizing the testing principles as follows:

Testing on the spot under the real train operation in CM /ATPM mode;

The position of driver operation handle reacting the traction force;

A digital electricity meter recording each consume in 3 seconds periodically.

3.2. AW0-3 Learning

Acquiring Characteristic Performance Curve of Traction Force (aw0, aw1, aw2, aw3) is the basic requirement for traction computing, for they have a different loads in real train operation involving in traction force directly. So, approximately estimating their weights by four kinds of load conditions as table 1 shown ,and get the real curve that each train must perform the four groups testing firstly by simulation and then on the spot running.

Table 1. Four exteme weights evaluation of the train

Statue	Number of Passengers	weight(t)
AW0(no load)	0	220
AW1(full seat)	336	240
AW2(overload,6men/m2)	1860	331
AW3(overload,9men/m2)	2592	375

(Assume each passenger weights 60kg)

According to Newton’s theory, the train acceleration curve must be a straight line under a certain load, which is a consistent rule in RBR. But in fact, the real curve isn’t a direct line, even not with a simple fitting function, for the train traction force varies depending on different conditions such as train speed and load as fig 2 shown. The more troubled problem is there isn’t consistent cooperation with load varying, so the train acceleration curve must be plotted under different loads, especially with extreme loads- from empty load AW0 to overload AW3. When they are used for traction calculating, interpolating the approximate value is a feasible way from the similar loads.

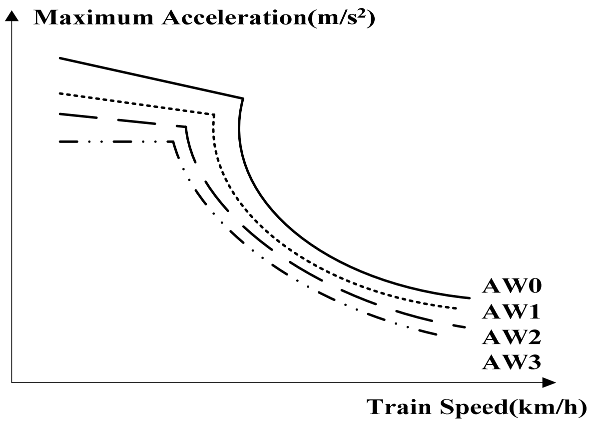

Figure 2. The four groups of traction force in exteme weights

That is a normal and common way for evaluation the URT train speed due to the inconsistent rule, from which such RBR system has to just find a approximate value instead. Let’s think over CBR system, for each case can be drilled for the rule, the four curves of extreme load can be easily used in our CBR system for they stored with cases. Furthermore, each case acquired from the real implicates the whole running conditions for the train operating, and later they can be reasoning in CBR system cycles in spite of those trouble constraints.

3.3. Results with Outlook

In our experiments, the URT train runs from Station A to Station B about 1300m, whose basic slope data and speed limits are shown in fig 3. Considering of the control for energy-saving within a effective passenger’s travel speed, the basic rules and application conditions on energy-efficient control of train operation are concluded as follows:

The coasting mode is the key for the train energy-saving control, which is fully used if it is possible.

The full power mode is applied when the train needs to run at the maximum accelerated speed (from the starting stage and also from a low speed to a high speed) considering of time limitation.

The full braking mode is mainly applied to the braking deceleration stage before the train stops for the time limitation.

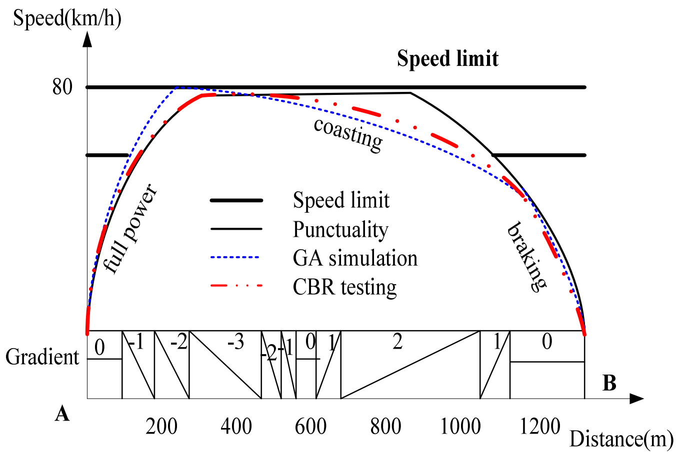

Figure 3. different running speed curves in three methods

The proposed running curve can be divided into such stages: from start up full power, coasting1, (routing full power, coasting2), to end up braking. Depending on train speed and load, the maximum train acceleration usually varies; real cases are merged in each running statement for the same routing stage, which is classified inML- RS module; RBF is used to find the most similar case for the optimized operation in each stage, which at last is changed into a feasible operation method for population.

As table 2 indicates, CBR routing can be used for real URT train operation in 26.92% energy reduction ratio, and can meet the time limitation demands. Although GA Simulation has a better performance for they can touching the speed limit while real running must have a few speed surplus caring about train braking caused by safety problem, in other words that is an idealist value which can encourage us promote our methods furthermore.

Table 2. Performance in different operation

Operation mode	Energy consume(kWh)	Time(s)
Punctuality real operation	57.239	84
GA optimized simulation	32.327	95
CBR Real testing	41.831	95

4. Conclusion

Many researches have found different ways for URT optimal running, to minimize the energy for propulsion from both analytical and numerical methods, and drawn a lots of useful design for industrial implementation. The train speed is affected by many inconsistent factors with uncertain constrains, which are so complex that researches have to omit some constrains for simplify their model. In order to achieve such multiplex tasks under complex environments with complicated operation, our case intelligent system has a good flexibility to integrate many components, which can use synthesis reasoning technology from both RBR and CBR for problem-solving. The system performs well on the spot and indicates that our future work to tune the speed better from system control.

Acknowledgments
This research is financially supported by the China Postdoctoral Fund of HFUT, and the Natural Science Project of Jiangsu Province YJ2017012. All the persons involved in the research projects are thanked for their help.

References

[1] I. A. Asnis and A. V. Dmitruk, Solution of the problem of the energetically optimal control of the motion of a train by the maximum principle, U.S.S.R. Comput. Math. Math. Phys., 25 (6): 37–44, 1985.
[2] R. R. Liu and I. M. Golovitcher, Energy-efficient operation of rail vehicles, Transportation Research Part A: Policy and Practice, 37 (10): 917–932, 2003.
[3] E. Khmelnitsky, On an Optimal Control Problem of Train Operation, IEEE Transactions on Automatic Control, 45 (7): 1257–1266, 2000.
[4] P. G. Howlett, P. J. Pudney and X. Vu, Local energy minimization in optimal train control, Automatica, 45 (11): 2692–2698, 2009.
[5] R. Franke, P. Terwiesch and M. Meyer, An algorithm for the optimal control of the driving of trains, in Proceedings of the 39th IEEE Conference on Decision and Control, 2000: 2123–2127.