URT train energy-saving scheme optimized on case intelligence using SRS and RBF

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Abstract. Great challenge of energy consumption in urban rail transit (URT) has been attracting much greater concerns for its more complicated impact factors. To find the energy-efficient train speed curve is the essential way for energy-saving propulsion, but it is a difficult task full of uncertainty knowledge involving in real-time train operation, which is a complicated CSP (constraint satisfaction problem) with so much inconsistent constrains that cannot be solved effectively. The paper proposes case intelligence based on CBR (case-based reasoning) to acquire the train operation preferences from the former stored cases, and constructs a flexible system integrated with efficient machine learning methods for synthesis-reasoning. The subsequent research indicates that similarity rough sets (SRS) and radial basis function network (RBF) can conquer the complexity and uncertainty of real problem, for the experimental results indicates that the hybrid system gives a fine performance as shown in real-time URT train operation.

1. Introduction

The problem of energy consumption is getting more and more serious in urban rail transit (URT), which takes large quantity of energy consumption. Considering of the traction power consumption is more than 60 percent of the total URT energy consumption, so high the consumption proportion is that it is an chief task how to efficiently reduce the traction power consumption for the train energy-saving. A lot of useful studies from optimal control have been carried out from both analytical and numerical methods since1960s. For example, [1-3] determine an optimal driving strategy with a generalized equation of motion to find necessary conditions, or finding key equations by applying maximum principle analysis; due to the complexity of the mathematics analytical methods above, [4-6] have constructed large of simulating methods on energy-saving by computer programming evolutions, such as fuzzy control, genetic algorithm, artificial neural networks, and ant colony optimization, etc. to calculate the optimal reference trajectory by formulating the optimal train control problem.

Through many years researching, many factors have been found affecting train energy consumption such as well-known traction braking performance, train dead weight, running speed, signaling block mode, train operation mode, and many uncertain factors which are difficult to obtain the optimal solution due to the complexity of the real train operation. For example, traction force and frictional resistance cannot be described numerically for its adhesion state ranges with the wheel-rail humidity also with wheel tread surface changing [7]. So the precise calculation is still a difficult task even though many
progresses have been taken, for they either assume running in specific conditions or simplify the calculation omitting certain constrains.

So many impact factors are full of uncertainty and not exactly described in the train energy-saving propulsion problem, which indicates that the problem-solving cannot be used only by the traditional Rule-based reasoning (RBR). From the view of cognitive, analogy is an important reasoning model of human sense, which domain experts uses for decision-making with more imaginative thinking - Case-based reasoning (CBR), performs inferential study strategy to process knowledge reasoning from the similar former cases and appropriately adapts for the new problem-solving. CBR has its unique reasoning and caused widespread concern in AI especially in weak-knowledge domains but full of empirical knowledge like laws, fault diagnosis, decision making and cooking, etc.[8], so we propose to construct case intelligent system based on both CBR and RBR to real URT energy-saving operation problem-solving.

2. Smooth speed profile learning

2.1. Uncertain and inconsistent factors
Wheel-rail adhesion state is one of the important factors affecting the normal traction-braking performance full of uncertainty. The wheel rolls on the rail while the train brakes, the contact between the wheel and rail is neither static nor sliding, it is the Adhesion state - the phenomenon of keeping the wheel moving in contact with the rail. But if the traction-braking torque on the wheel over the maximum adhesion that wheel-rail can provide, terrible disasters occurs such as wheel-rail abrasion, train traction-braking force degradation- idling-sliding phenomenon happens. Adhesion coefficient is an index used to indicate the adhesion state between the train wheel and the rail, which looks like a perfect result for traction computing, unless we pretends the adhesion state to be in a stable surface.

The adhesion coefficient is affected by many factors such as train running speed, climatic conditions, wheel and rail surface condition, so it is difficult to have a theoretical formula of adhesion coefficient in RBR. Many adhesion control methods based on the wheel-rail adhesion state observation is proposed for computing, with a large number of tests have to be used to obtain empirical calculations and formulas in many countries. Such inconsistent can be seen as the vehicle ‘Characteristic Performance Curve of Traction Force’, which describes in four special parameters (aw0,aw1,aw2,aw3) for traction computing as shown in fig 1. Each of the real Curve isn’t a direct line, and the more troublesome problem is a inconsistently corresponding with load varying, so the train acceleration Curve must be plotted under different load, especially with extreme load from empty load AW0, AW1(full seat), AW2(overload,6men/m2),to overload AW3(9men/m2), for the train traction force varies corresponding with train speed and load.

Figure 1. The four extreme groups of traction force and hybrid system construction
2.2. Hybrid system construction

As well known, URT signaling system - Automatic Train Control (ATC) system - consists of ATS, ATP, ATO subsystem and Data Communication System (DCS) subsystem (main part as computer system). ATO system can support multiple speed profiles to meet the requirement of punctual, passenger comfort and energy saving, while DCS coordinates with the designs of vehicle, track, architecture, communication and routing operation etc.

Many large-scale rail transit companies have invested a lot in the research of subway train control algorithms to meet the Green Energy needs, and current subway ATC system has already proposed several “interesting” speed operation curves to facilitate the speed selection. For example, in Shanghai, Nanjing and Hefei Metro Line, the speed curve of trains includes four grades operation- Grade 1 is the full speed mode, usually taken at peak times; Grade 2 is the coasting mode; Grade 3 and Grade 4 are the in 75% and 60% speed limits respectively.

According to their technical documentary reference, their energy-saving speed curve is calculated offline by using the same simulation software with the acceleration curve depending on Metro line and vehicle conditions. They are also calculated by simplifying model and omitting some constrains, for they cannot be accurate calculating by a formulation through RBR. Moreover, simulation should be validated in real-time testing ahead of the normal operation, by means of the real operation data adaptation to revise its Empirical formulas. such steps indicate their ‘optimal energy-saving’ curve is drawn with empirical calculation and empirical learning, from which we can perform case intelligent system through VOBC for its similarity measurement.

In our case intelligent system, each case implicates a real time running operation, which can describe with such attributes: Case= \{start point, end point, start point speed, end point speed, line conditions, passenger flows, Traction Force, etc.\}. so, they themselves involves empirical knowledge from experts, and can be naturally drilled in ‘rule’ knowledge through many kinds of machine learning methods. Excellent flexibility of CBR system indicates that CBR is a hybrid system “for building knowledge-based systems, rather than an isolated technique”. The system can adopt modular components not only to satisfy the performance requirements of various tasks, but also to realize system gradual expansion suitable for many ML tools development.

2.3. Case transfer learning

Considering the characteristics of the train energy-saving, train speed curve must be optimized with the least propulsion and brakes no mentioned for the comfort of the passengers. To perform the smooth speed profile, learning ability is the most important embodiment of human intelligence, though RBR is common and normal process, CBR is usually used unconsciously for its creative thinking. So we can perform knowledge learning strategy for URT train optimal propulsion based case-intelligence as follows:

1) Suppose a URT train serials run from station A to station B with their real speed curves stored in case library as \(S_1, S_2, \ldots, S_n\) , so the best speed curve \(S_i\) with the least energy consumption can be worked out and reused for new problem-solving in CBR process by case adaptation for they have the most similar running constrains.

2) Based on similarity criterion, optical speed learning process can perform from both itself and others, from itself the base case is drilled out while it has the most similar conditions, from the others in the same kind of train while they also have the most similar dynamic presentation.

3) Through DCS, base case can also be proposed from the same kind of train and similar speed curve under different route by transfer learning, either from the different kind of train ideally if the learning ability can meet the ATO running demands.

For the application of naive CBR method does not guarantee the system efficiency, the main goal of machine learning research in our system is to develop computational methods that enable a variety of learning forms, drilling rules especially the ability to generalize knowledge from real operation data. Hybrid system uses all of the three methods in our practicing experiment, (1) parallel reasoning and choosing the better result; (2) Mutual conversion; (3) Master-slave auxiliary reasoning.
3. experiments with outlook

3.1. Features extraction

Rough Sets is a mature KDD tool for information processing, whose basic task is to construct a suitable granularity to decrease the system complexity; and we propose Similarity Rough Sets (SRS) for our Case Intelligent system not only for the same similarity measurement, especially for which our case attributes in real URT operation are continuous and must partition in discrete value. Huge train operation cases should be dealt with SRS for many different purposes, such as attributes reduction in real domains, core attributes searching, inconsistent knowledge conquering, etc. As well known, though core attributes are easily drawn for RS, attributes weights as prior knowledge are important and often given by domain experts from their experience for long-time practice intuitively, so we objectively extract our weights for all attributes directly through the drilling down the cases.

Table 1. The discernibility matrix

|    | X1     | X2     | X3     | X4     | X5     |
|----|--------|--------|--------|--------|--------|
| X0 | b,c,e  | b,c,d  | a      | a,b,c,d| a,b,c  |
| X1 | a,b,c,d,e| c      | b,c,d  | a,b    | a,d,e  |
| X2 | a,c,e  | b,c,d,e| b,c,d,e| a,d,e  | a,b,e  |
| X3 | a,b,c,e| a,b,d,e| c,d,e  | b,d,e  | a,b,d,e|
| X4 | a,c,d,e| a,d    | b,c    | b,d    | e      |

Firstly, Discretizing train speed, distance, line conditions and train load, etc. according to their attributes’ range, and then the normal binary decision table can be described for traction propulsion force on/off as shown in table 1. \{a,c,e\} can be easily acquired as the core attributes with the reduction \{a,b,c,e\} or \{a,c,d,e\}. But we realize that each item has its own weight in decision-making, and the core \{a,c,e\} cannot be the same weight for they occur in different frequency, each attribute weight can be accurately objectively calculated by the following algorithm:

- Classifying each element in the discernibility matrix, on account of the number of items contained in the classification attribute. Marked each the attribute as M\(_1\), M\(_2\),…, M\(_m\), which reflects the grade m, m-1… 1, assuming M\(_1\) is the highest grade, and M\(_m\) the lowest grade.
- Counting for each property item in the collection of each type, and calculating the number of occurrences of each item beginning from M\(_1\) till the end of the entire cross.
- Comparison of their counts for each attribute from M\(_1\) to M\(_m\), if the counts are the same, the comparison of their number in the M\(_2\) must be done, and so on. while the number of items in the count is more than any other items within each M\(_i\), this means the attribute representing the item has the higher property and weight.

Finally the weights for each attribute are- (a:0.367, b:0.078, c:0.291,d:0.063, e:0.201). (b, e) are less important, but cannot be ignore for they are important impact factors in our real operation cases, which many researches are troubled in finding all the time, and their weight values should be used in the subsequent experiments, such as classifying cases for predicting, optimal case selection.

3.2. Cases selection

Train operation cases must be partitioned correctly for case stored, case revision, or reusing for rule extracting, etc. so two familiar UCI machine-learning-databases like running cases are chosen to validate our case-intelligent system. The one is much close to our interval cases as its own operation, the other is simulated as its own multiple operations or the same kind of vehicles’ operations. Due to the much more complex factors inferring the energy-saving, the cases must be classified correctly and the most similar case be selected for optical case, which are shown as the following steps.

1. SVM classification. “Breast-cancer-wisconsin” (699 Instances, 9 Attributes plus the 1 decision attribute) and “Mushrooms” (8124 Instances, 22 Attributes plus the 1 decision attribute as edible or not) can be all simulated for binary decision as decision attribute. Cases are represented for a real running
operation for Metro Line, with all operation parameters shown on TOD or instruments, thus missing data or uncertain decision attribute cannot exist in our cases. SVM classifies cases and gets perfect results with all correction in a flash time, which indicates the method is feasible and reliable.

(2) RBF case retrieving. As well known the optimal speed curve is in three operation modes which is full propulsion mode, coasting mode and full braking mode, so “Iris Plants Database” is also downloaded from UCI ML Repository, for it has three classes the same with our real operation. The four attributes are represented the key impact factors as extracted feature values from the former SRS, where 6 records are selected randomly from the database as cases library, with 3 records as target case marked in t1-t3. Experimental results are shown in table 2, with the weights of each impact factors computed. As the most important process in CBR cycle, case retrieval is the key and RBF retrieval model can be seen in [9] also with the weights of each attribute are computed for case selection. Those results suggest our synthesis reasoning can combine various reasoning principles and integrate many ML methods useful to enlarge the system’s ability.

| id | At1 | At2 | At3 | At4 | C | t1   | t2   | t3   |
|----|-----|-----|-----|-----|---|------|------|------|
| 1  | 4.7 | 3.2 | 1.3 | 0.2 | 1 | 0.99912 | 0.00643 | 0.00746 |
| 2  | 5.1 | 3.7 | 1.5 | 0.4 | 1 | 0.21755 | 0.00380 | 0.20341 |
| 3  | 5.8 | 2.7 | 4.1 | 1.0 | 2 | 0.00411 | 0.90981 | 0.00002 |
| 4  | 6.8 | 2.8 | 4.8 | 1.4 | 2 | 0.00516 | 0.78041 | 0.00013 |
| 5  | 6.2 | 3.4 | 5.4 | 2.3 | 3 | 0.00186 | 0.00274 | 0.81150 |
| 6  | 6.1 | 3.0 | 4.9 | 1.8 | 3 | 0.00135 | 0.00679 | 0.56827 |
| t1 | 4.3 | 3.0 | 1.1 | 0.1 | 1 |      |      |      |
| t2 | 5.8 | 2.7 | 4.1 | 1.0 | 2 |      |      |      |
| t3 | 7.7 | 3.0 | 6.1 | 2.3 | 3 |      |      |      |

3.3. Strategy realization
Our real experiments are contributing the real-time operation on the spot, where to meet the train safety demands is the chief task. Due to complexity of the URT train RAMS requirements, our software cannot be directly inserted into VOBC system software for performing the real operation, and train operating mode should be mentioned here. The train is under the direct manual control of the Train Operator but supervised by the ATP system with the information shown on the TOD. So our experiments are taken in CM or ATPM mode; A digital electricity meter is recording the real-time energy consume in 3 seconds periodically; and only the position of driver operation handle can react the traction force.

![Figure 2. Different running speed curves in four methods](image-url)
In our real operation, the URT train runs from Station A to Station B about 1300m, whose basic slope data and speed limits are shown in fig 2. Firstly, simulation must be done for system permitting, our CBR system imitates the running which get almost the same curve with GA simulation as most researcher done, so the two curves have to be drawn as one. Considering of the control for energy-saving within a effective passenger’s experience in real time operation, the basic rules for the control of train should be drilled out from the ML methods, where real cases are merged in each running statement and translated into a feasible operation method for driver. As table 3 indicates, CBR routing can be used for real URT train operation in 26.92% energy reduction within more time 13.10%. Though GA and CBR simulation has a better performance for they can touch the speed limit while real running must have a few speed surpluses caring about train braking caused by safety problem, in other words that is an idealist value which can encourage us promote our methods furthermore.

| Operation mode            | Energy consume(kWh) | Time(s) | Energy reduction |
|---------------------------|---------------------|---------|-----------------|
| Punctuality real operation| 57.239              | 84      |                 |
| GA optimized simulation   | 32.327              | 95      | 43.52%          |
| CBR simulation            | 32.327              | 95      | 43.52%          |
| CBR Real running          | 41.831              | 95      | 26.92%          |

4. Conclusion

The problem-solving of optimized URT energy-saving operation is a extremely complex CSP, which delays on the realization of their variables and constraints, causing many researcher have to simplify their model or in a special condition for they are inconsistent with full of uncertainty. Our case-intelligent system has excellent flexibility to integrate many components as ML tools to solve such problems easily, which performs well for cases features reduction, attributes weighting and case selection, especially for the dealing with uncertainty with inconsistent knowledge, so the better results are guaranteed for the real URT train energy-saving operation.

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