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Simultaneous Optimization of Energy Consumption and Train Performances in Electric Railway Systems

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Abstract: This paper focuses on obtaining an optimal speed trajectory for a train regarding its energy consumption as well as its travelling time simultaneously. Dynamic model of a train on a predefined track including slopes and tunnels is developed. Considering complexity of analytical optimization method for antithetic objectives, NSGA-II and MOPSO evolutionary algorithms are employed to solve the multi objective optimization problem. A novel control index is defined instantaneously so that the important issue of passenger comfort is taken into account specifically. As a case study a Voyager train parameters are used to simulate the whole system via MATLAB software. Simulation results show the efficiency of the proposed methods to find the desired optimal speed trajectory as well as providing suitable passenger comfort.

Keywords: Energy efficient strategy, Multi Objective Particle Swarm Optimization (MOPSO), Non-dominated Sorting Genetic Algorithm (NSGA-II), Railway Transportation System, traveller Comfort

1. INTRODUCTION

Increasing transportation expenses as a sequence of ever growing population in most of the world countries has kept intercity railway system as a superior transportation system. Finding an efficient optimal control to minimize train energy consumption is a crucial issue in railway engineering.

L. Yang et al. (2012) researched on a mathematical model with a predefined track. He applied coasting control strategy to the model to find optimal motions of the train. Sh. Lu et al. (2011) investigated the potential of applying advanced power management strategies for a DMU (Diesel Multiple Unit) train. These vehicles have multiple diesel units commonly operating in homogenous manner. This paper evaluates the possibility of energy saving through independent operation of motors using DP (Dynamic Programming) method.

Accomplished studies can be divided into two major categories based on employed control strategy: coasting and global control. Coasting control is used to modify energy efficiency in a train in coasting mode. For instance, to determine specific points where in optimal speed trajectory is assured, if traction motors provide no torque [K. K. Wong et al. (2001), M. Kang (2011), D. Yong et al. (2011)]. Global control can be very complicated since it uses all available signals and suffers from a heavy calculation burden. Proposing a graph, Sh. Lu et al. used DP, ACO (Ant Colony Optimization) and GA (Genetic Algorithm) methods to generate an optimal speed profile with minimum energy consumption under time constraints [R. Liu (2003), R. Chevrier et al. (2011), Sh. Lu et al. (2013)]. Their results showed that DP generates optimal speed trajectory with a better performance but a heavier calculation burden as well.

Since two problems of minimum energy consumption and minimum travelling time are in a conflict, using analytical methods to minimise the two purposes simultaneously is difficult. Therefore applying evolutionary methods to such problems can lead to satisfactory results. In this study, we consider the train as a plant that is able to reach the desirable destination from a certain origin. A sequence of signals including breaking, coasting, cruising and motoring signals are considered as inputs to the plant. A $k \times n$-*node* graph implying n nodes and k candidate velocities in each zone is assumed. Optimal mode in each zone must be determined so that the train can track the optimal node by an efficient driving strategy. Two NSGA-II and MOPSO multi objective evolutionary algorithms (MOEAs) are employed here to realize optimal train speed trajectory. Moreover, a new solution is proposed to improve passenger comfort during travel, especially while breaking.

This paper is organized as follow. In section 2, modeling procedure, objective functions and a searching graph will be introduced. In section 3, control index assignment approaches and a driving strategy will be discussed and two methods in multi-objective optimization will be implemented and their resulted pareto fronts and optimal speed trajectories will be shown and compared together. Finally, a conclusion will be drawn in section 4.

2. PROBLEM DEFINITION

2.1 Vehicle Movement Physics

Modelling of rail vehicles dynamics in order to compute the velocity distance and time status of a moving train on a certain track is accomplished under a number of constraints such as system signalling and traction devices specifications. The equation of motion is based on newton's second law as:

$$M_{eff} \frac{d^2x}{dt^2} = f_T - R - Mg\sin(\alpha) \tag{1}$$

Where parameters are defined as below:

f_T	Traction force (N.m)
M_{eff}	Effective mass (kg)
R	Train resistance (N)
g	Gravitational force (N)
$Mg\sin(\alpha)$	Negative force due to path slope
x	Train distance (m)

In addition to stationary components, trains are included some Rotatory components that influence the train effective mass. Hence, rotary allowance should be considered as well to increase the accuracy of calculations [Sh. Lu (2011)].

$$M_{eff} = M(1+\tau) \tag{2}$$

In (2), rotary allowance τ , is usually assumed to be less than 0.2 [Sh. Lu (2011)].

Operational control modes are generally categorized to four modes: motoring, cruising, coasting and braking. During motoring mode which in turn is divided to full motoring and partial motoring, vehicle velocity is switched from low speed state to high speed state. By cruising mode the velocity is held at a constant level. In the coasting operational control, traction motors produce no torque meaning that the energy consumed by traction motors is zero. In practice the acceleration would be influenced by total resistance of the train and the gravitational effect, in this situation. Selecting the coasting point where in the train enters the coasting mode has a remarkable effect on total service quality and energy consumption [K. K. Wong et al. (2004)]. During the braking mode including full braking and partial braking, train speed decreases to reach a lower speed limit and to stop at the station as well. Critical requirements of braking mode operational control are to assure that the train speed always remains under certain level and also the train arrives at the station with zero level speed. Several methods are introduced to determine the exact point of braking. They assume a train at the eventual point and move it inversely by an analogous traction force to obtain a speed trajectory. The resulted trajectory will be then intersected to the normal train speed trajectory. The intersection point will be the exact braking point [S. Hillmansen et al. 2007]. This method is efficient when the train is to brake by a constant, not a varying, braking ratio. In this paper, we propose a new method applying a virtual braking process in each moment once the train enters the braking area. The proposed method determines the exact braking point, while it is efficient for various braking ratios.

2.2 State Equations and Objective Functions

Governing equations of jth train can be stated according previous chapter contents as:

$$\begin{bmatrix} \dot{x}_j \\ \dot{v}_j \end{bmatrix} = \begin{bmatrix} v_j \\ \frac{1}{M_{eff}}(f(u_j(t), v_j(t)) - r(v_j) - G(x_j, v_j)) \end{bmatrix} \tag{3}$$

In (3) x_j, v_j, and u_j represents positions, velocity and input signal of the jth train, respectively. r implies the resistance against the train movement which is shown in (4) and f, expressed in (5), is the applied force to train wheels. G is longitude force imposed by tunnels, slopes and curvatures of the track for jth train with length of L. longitude force is shown in (7).

$$r(v_j) = A + B \cdot v_j + C \cdot v_j^2 \tag{4}$$

A, B and C are empirical coefficients called Davis coefficients [B. P. Rochard et al. (2000)].

$$f = u_j(t) \cdot TE_j(t) \tag{5}$$

$TE_j(t)$ is the maximum traction effort and can be stated as:

$$TE_j(t) = \frac{\mu \cdot P_{n_j}}{v_j(t)} \tag{6}$$

Where in μ and P_{nj} are friction factor and nominal power of traction motors in jth train. Longitude force per mass unit is expressed as:

$$\begin{aligned} G(x_j, v_j) = {} & mg\sin(\alpha(x_j)) + f_C(R(x_j)) \\ & + f_t(L_t(x_j), v_j) \end{aligned} \tag{7}$$

In (7) $\alpha(x)$, $R(x)$ and $L_t(x)$ are the slope, the radius of the curve, and the length of the tunnel along the track, respectively. $f_C(\cdot)$ and $f_t(\cdot)$ are the curve resistance and the tunnel resistance. These are given by experimental equations. A number of sample resistances are obtained by Roeckle [Y. Wang et al. (2011)] as follows:

$$\begin{cases} f_C(R(x_j)) = \dfrac{6.3}{R(x_j) - 55} m \quad for \quad R(x_j) \geq 300m \\ f_C(R(x_j)) = \dfrac{4.91}{R(x_j) - 30} m \quad for \quad R(x_j) < 300m \end{cases} \tag{8}$$

A train confronts a new aerodynamic resistance once it enters a tunnel. The aerodynamic resistance extent is related to the tunnel shape, the smoothness of tunnel walls, the exterior surface of the train, etc. [Y. Wang et al. (2011)]. The resistance can be expressed as follow:

$$f_t(L_t(x_j, v_j) = a_t(L_t(x_j)) \cdot v_j^2 \quad (6)$$

Multi-objective problem of simultaneous optimization the train energy consumption and travelling time can be written as a set, Φ , including n objective functions to be minimized.

$$\Phi = (\varphi_1, \dots, \varphi_n) \quad , \quad n \le 2 \quad (7)$$

The first objective function, φ_1 is related to energy minimization, meanwhile the second objective function φ_2 explores the minimum travelling time.

$$\varphi_1 = \min E \quad (8)$$

$$\varphi_2 = \min T \quad (9)$$

Consumed energy of the jth train is expressed as:

$$E_j = \int_{t_{j0}}^{t_{jf}} P(t)dt = \int_{t_{j0}}^{t_{jf}} f(u(t), v(t)) \cdot v(t)dt = \int_{t_{j0}}^{t_{jf}} u_j(t) \cdot TE_j(t) \cdot v(t)dt \quad (10)$$

Travelling time of the train equals summation of the total time durations needed to travel between two zones in a track with n zones. This statement is shown in (11).

$$T_j = \sum_{k=1}^{n} T_{jk} \quad (11)$$

In (11) T_{jk} represents the time taken to the jth train to pass the kth zone. Constraints and boundary conditions on the problem are as follows:

$$x_j(t_0) = x_{j0} \quad , \quad v_j(t_0) = 0 \quad (11)$$

$$x_j(t_f) = x_{jf} \quad , \quad v_j(t_f) = 0 \quad (12)$$

$$-1 \le u_j \le 1 \quad (13)$$

$$v_j \le v_{j\max}(x_j) \quad (14)$$

v_{jmax} is allowable speed of the jth train determined by the traffic control system, ATP, in each zone.

2.3 Graph Construction

In this paper we develop a $k \times n$-node graph representing a certain track with n zones and k candidate speeds for each zone. The graph is depicted in fig. 1. In each of the defined zones, the target speed must be determined so that the train can track the speed. The outcome of the optimization is the target speed for every zone.

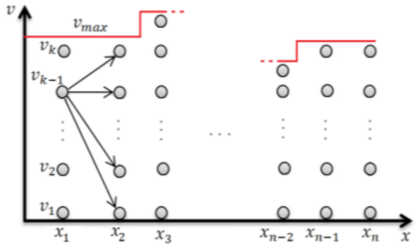

Fig. 1. Graph construction

If the initial state of the train is known, then a state switch can be occurred to obtain the new state. See equation (15).

$$\psi_0 = \{x_0, v_0, t_0\} \xrightarrow{f_T} \psi_1 = \{x_1, v_1, t_1\} \quad (15)$$

The state transition is done by making a change in the traction power. This achieved by the driver or ATO as a control index. As a consequence, a proper sequence of control indexes shall be generated for different state transition.

Table 1. Voyager train parameters

Maximum *TE* (*kN*)	146.8
Maximum Power (*kW*)	1568
Mass (*tones*)	213.19
A	3.73
B	0.0829
C	0.0043

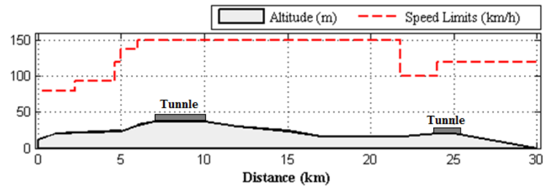

Fig. 2. Track profile, speed limits and tunnel places

2.4 Case Study

As a case study, a Voyager type train [8] with parameters shown in table 1 is used in this paper. Track length is assumed to be 30 km with the profile, speed limit and tunnels place as in fig. 2.

3. SIMULATION AND RESULTS

3.1 Control Index with traveller Comfort factors

In the literature travelling comfort is often ignored when developing optimal speed profile. This issue is of a greater importance while the train is in braking or motoring mode. Generally, the train driver is engaged with three important devices to control the train: a lever to control the traction force ratio, a lever to braking ratio and the ATP system to determine the speed limit.

Operational control input is defined as:

Table 2. Operational modes by driver

	Motoring	Cruising	Coasting	Braking
$u_j = 1$	■	■		
$u_j = 0$			■	
$u_j = -1$				■

$$u_j'(t) = u_j . k_C(t) \tag{16}$$

u_j is selected by driver as table 2. k_C(t) is a new defined coefficient in this paper to determine the control index. k_C is decided from (17) while the driver set the operational control on motoring and cruising modes and from (18) when the operational control is set on braking mode.

$$k_c(t) = \frac{v_{ai} - k_m v_i(t)}{v_{ai}} \tag{17}$$

$$k_c(t) = 1 - \left| \frac{v_{ai} - k_b v_i(t)}{v_{ai}} \right| \tag{18}$$

Based on the equations (18) and (18), k_m,k_bϵ[0,1] are considered as comfort criteria factors. As k_m approaches to zero, the less comfort criteria is resulted. Fig. 3 demonstrates the train acceleration in motoring mode for several k_m values. It is observed that selecting a proper k_m can improves significantly the passenger comfort in motoring mode.

Another challenging issue with a great influence on passenger comfort is lack of a satisfactory braking process. However, in literature, only a negative traction force is regarded as braking process while it has a negative effect on passenger comfort. By means of the developed coefficient, k_C, shown in (18), braking mode ratio at each instant is set according to k_b. The selected k_C manages the braking mode so that the train stops at the station with a smooth decreasing negative acceleration. Fig. 4 shows the acceleration curves for different k_bs. It is obvious that for k_b= 0.1, negative acceleration during braking mode has a lower extent therefore it benefits a better passenger comfort compared with when k_b= 1.

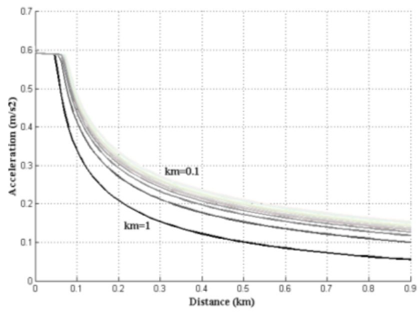

Fig. 3. Acceleration curves due to various k_m values in motoring mode condition

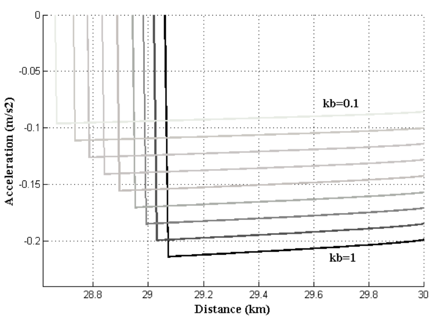

Fig. 4. Acceleration curves due to various k_b values in braking mode condition

3.2 Driving Strategy

In order to generate speed profile, track is divided into n zones. Next three specific speeds for each zone are derived from the solution multi-objective problem namely v_{ei}, v_{ai} and v_{xi}. For each zone two sections are considered: the first section contains two speeds of v_{ei} and v_{ai} that are entrance speed and candidate speed, respectively. The second section contains v_{ai} and v_{xi} that are candidate speed and exit speed, respectively. v_{ei} and v_{xi} are generated during speed profile generation while v_{ai} is obtained by applying multi objective evolutionary algorithm.

If v_{mi} is assumed to be the maximum speed corresponding to ith zone, which is defined by ATP system and track information, there exists following constraints for ith zone:

$$v_{mi} \geq v_{ai} \quad \forall i = 1,...,n \tag{19}$$

$$v_{ai} \geq 0 \quad \forall i = 1,...,n \tag{20}$$

The driver should only select $u_j \in \{-1, 0, 1\}$ to reach the target speed in each zone. Motoring or braking ratio is determined automatically by control index, k_C, in all instances. Here we employed two evolutionary multi objective algorithms, NSGA-II and MOPSO, to identify optimal speed trajectories. Optimization is accomplished for two antithetic objectives namely energy consumption and time travelling minimization.

3.3 NSGA-II Implementation

Non-dominated sorting genetic algorithm (NSGA-II) was introduced by K. Deb (2002) for the first time. This method is analogous to ordinary genetic algorithm but with two additional parts: non-dominated sort and crowding distance. In order to find the target speed in each zone, the speed is considered as optimization variable. To apply NSGA-II, following process must be done: Initialization step generate k chromosomes or vectors containing n random speed variables. Then fitness evaluation step calculates fitness value of speed vectors. In non-dominated sorting step a rank is assigned to each member. To measure the diversity of the members, crowding distance controlling parameter is considered. In the next steps, cross over and mutation are used to generate new offspring.

3.4 MOPSO Implementation

Coello Coello et al. (2004) developed multi objective particle swarm optimization (MOPSO). The fundamental procedure of the algorithm is the same as conventional PSO algorithm but the best particle and the best personal experience is expanded for more than one objective. Measuring the fitness for particles is the same as NSGA-II.

Fig. 5 shows the Pareto front corresponding to the NSGA-II under various numbers of members and iterations. As it can be seen, Pareto front members are in convex form. Moreover, the population is of a suitable diversity because it covers the whole front. It should be mentioned that each member in the Pareto front represents a strategy including a vector of speed variables in decision space.

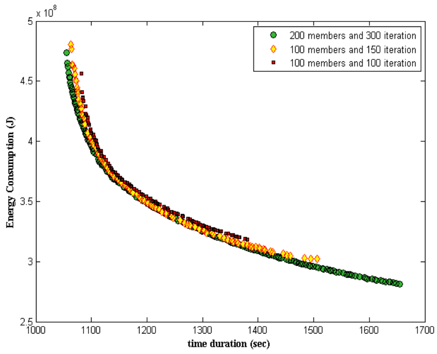

Fig. 5. Resulted Pareto front from NSGA-II method under various populations and iterations

Fig. 6 depicts the Pareto front corresponding to MOPSO algorithm. It can be seen in the figure that MOPSO results have a less diversity compared to NSGA-II. From Fig. 7 it is obvious that MOPSO algorithm is more efficient in longer trips whereas NSGA-II performs better in short trips, inversely. An off-line optimization procedure is accomplished in this paper. To select the favourable strategies, Pareto members are distributed inside a grid at first. Next the best strategy in the grid is selected according to the traveling time determined by the train schedule. The obtained strategy is then applied to the train by the driver assistant or ATO system.

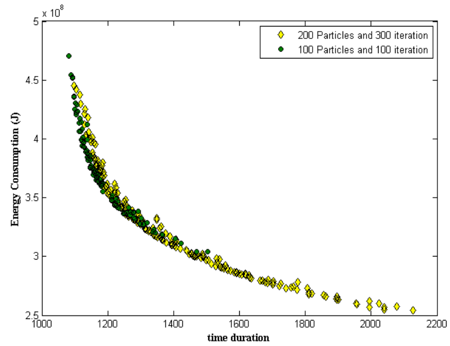

Fig. 6. Resulted Pareto front from NSGA-II method under various populations and iterations

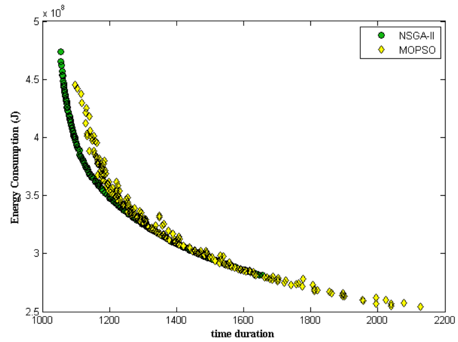

Fig.7. comparing the Pareto fronts resulted from NSGA-II and MOPSO methods

Fig. 8 demonstrates three strategies resulted from NSGA-II with three different travelling times of 1042, 1120 and 1250 seconds. This figure contains speed, position and acceleration profiles. In fig. 9 the same profiles as fig. 8 are depicted but the employed algorithm is MOPSO and the travelling times are 1070, 1190, and 1530 seconds. It is noticeable that MOPSO is about 10% faster than NSGA-II in operation for the same members and iteration. Resulted speed profiles in both fig. 8 and fig. 9 have a favourable smoothness. It also can be seen in these two figures that braking procedure are well performed for either stopping at the station or reaching to lower level speeds. Acceleration curves reveal that passenger comfort is regarded remarkably due to avoiding sudden acceleration changes. The position profiles show the precise stop point of the train at station. During speed decreasing to the target lower speed level, coasting mode is used as far as possible, however if the train speed fails to

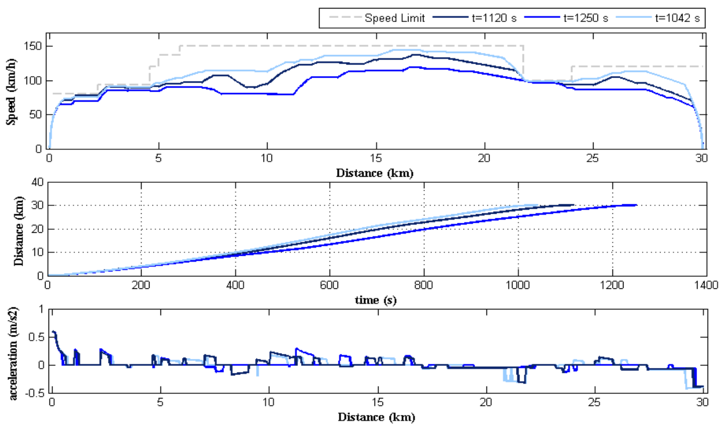

Fig. 8. Speed, position and acceleration profiles obtained from NSGA-II method

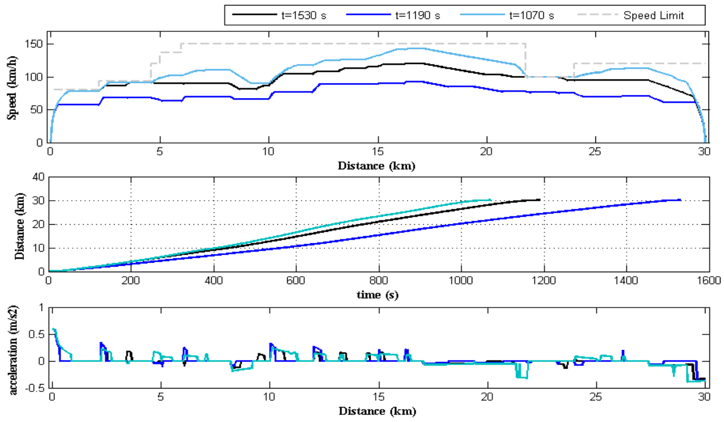

Fig. 9. Speed, position and acceleration profiles obtained from MOPSO method

reach the target speed during the critical distance, braking mode is used. To stop at the station, coasting mode is used before the braking mode as well.

4. CONCLUSIONS

Applying analytical strategies to solve a multi objective optimization problem can be too sophisticated, especially when the optimization objectives are in a conflict. Therefore numerical methods such as evolutionary algorithms can be very helpful in such conditions. In this paper a multi objective optimization problem was developed for a train to determine an optimal trajectory. Two antithetic objectives of energy consumption and traveling time extents were considered. NSGA-II and MOPSO evolutionary algorithms were employed to find the optimal trajectory. Simulation results showed that NSGA-II benefits a better diversity than MOPSO. It was also obvious from the results that MOPSO performs better for long-term journeys, meanwhile NSGA-II is more efficient for short-term journeys. Resulted speed profiles showed the efficiency of propose methods to solve the problem. In this paper some equations are developed to providing Passenger comfort.

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