Genetic Algorithm Based Bicriterion Optimisation for Traction Substations in DC Railway System

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ABSTRACT

This paper presents a genetic algorithm (GA) based method for bicriterion operating optimisation in DC railway systems, in order to achieve a tradeoff between high power recovery and uniform load sharing among traction substations (TSSs). Based on a multi-train movement simulation and line receptivity study, a scheme for optimally coordinating control of firing angles on the TSSs is proposed. The developed method can be used to any operating conditions, but the emphasis of this paper is on regenerative braking in DC railways. Simulation results have shown that much improvement on power recovery and load sharing can be achieved by using the proposed method.

1. INTRODUCTION

Cost effectiveness is always an important criterion in the operation of a modern rapid transit (MRT) system, and there is a great incentive to reduce the energy cost of railway operation for any MRT Corporation. In DC railway systems, trains are often equipped with both regenerative and rheostatic braking systems[1]. During regenerative braking, the released power is either used by nearby trains or returned to the power supply system through TSSs equipped with inverters [2]. On the other hand, should over-voltage occur, rheostatic braking will be activated. The recovery of power will thus be limited. In order to achieve maximum power recovery, rheostatic braking must be avoided whenever possible. In other words, some measures must be taken to prevent over-voltage from occurring.

In order to optimise both power recovery and regularity performance, a fuzzy-dwell-time-controller on each train at passenger stations was proposed [3]. In that paper, different settings of firing angles were studied to show their effects on power recovery, and simulation results have shown that optimal firing angles exist. Because both the system structure and operating condition change from time to time, the rheostatic loss during regenerative braking does not remain constant. Thus, the optimal firing angles with respect to power recovery will vary with system operating conditions. For full power recovery, the firing angles must be controlled dynamically so as to achieve their optimal values for all operating conditions. This is one of the two objectives this work will address.

The other objective of this paper is to deal with the load sharing problem among the TSSs. Generally, in absence of control, the recovered power of trains is returned to the power system mainly through their nearby TSSs. Thus the power handled by these nearby TSSs will be large, and sometimes can exceed their rated capacities. On the other hand, if the recovered power can be returned through all TSSs evenly, the power handled by each TSS is decreased [4]. To achieve this, it is necessary to control voltages at all TSSs by appropriately adjusting the firing angles. So, the two objectives are both related to how to control firing angles, but are different (one for power recovery, and the other for uniform load sharing). Thus, this is a bicriterion optimisation problem, that requires compromising between the two objectives.

Genetic Algorithm (GA) is a general optimisation method, and requires little knowledge about the problem to be optimised other than a cost or fitness function. In recent years, the application of GA to power systems has become an active research area, and many interesting papers have been published. For example, a GA-based economic dispatching method[5] and a GA-based bicriterion generation dispatching method[6] have been developed. GA is a powerful tool for solving very difficult optimisation problems and multiple objective optimisation problems. This paper shows that it is also suitable for solving bicriterion operating optimisation of electrified railways.

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2. SIMULATION OF ELECTRIFIED RAILWAY OPERATION

A typical electrified railway system consists of the AC substations, TSSs (with or without inverter) and other components such as trains, tracks, passenger stations, and control and signalling systems. The Object Oriented Technology [7] is applied in the simulation of the electrified railway operation. The simulation model consists of 3 main modules, namely, the railway operation module, the power supply module, and the AC/DC load flow module. These three modules are: 1) the railway operation module that simulates the control effects and events occurring in railway operation involving elements such as trains, tracks, and passenger stations; 2) the power supply module that simulates the operation of the AC substations and TSSs; and 3) the AC/DC load flow module that gives the electrical status of the railway operation. The schematic diagram and the simulation modules for the electrified railway operation simulation are shown in Fig. 1 (a) & (b), respectively.

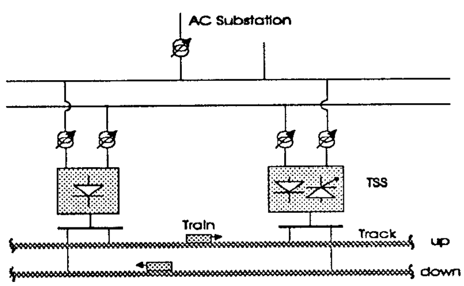

Fig. 1(a): The schematic diagram of electrified railway operation, and

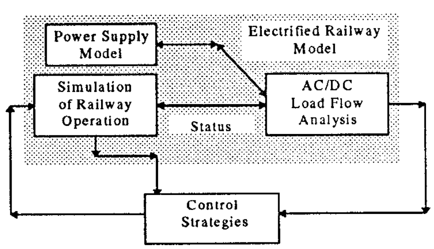

Fig. 1(b): The simulation model for electrified railway operation.

2.1. Characteristics of the DC Electrified Network Configuration

A DC electrified railway system has the following features:

a) **Continuous variations of the position and power of train (load buses):** Trains move and the power required by them changes with time. This power is either consumed or generated, which depends on the trains' operating modes: motoring or regenerative braking.
b) **Large system and train voltage variations:** In electrified railway networks, voltages can vary by +20% to -30% from the nominal value [8]. In conventional power networks, permitted variations are generally within the ±10% range.
c) **Nonlinear mathematical models:** For example, inverters are nonlinear elements, and the mathematical model describing the operation of trains is nonlinear too.
d) **Many constraints:** These include upper and lower limits of voltages on each TSS and on each train, constraints on each TSS capacity, constraints on the harmonic content produced by each inverter, and constraints on power factors.

These features require a flexible and robust optimisation beyond the capabilities of conventional optimisation methods. As stated above, GA is suitable for solving this problem.

2.2. Train Movement Simulation

The simulation is based on the following conditions:

a) The power consumption of each train is assumed to be dependent solely on its position.
b) Likewise, each train speed is a sole function of its position.
c) The relationship between the power consumption and its position is obtained from prior simulation of train dynamics [9].

Based on the above conditions, the consumed/generated power of each train is obtained from a prestored database for any simulation time. Power flow computation is run to evaluate the operating state, such as the voltage, power and current at any point of the electrified railway system, and the line receptivity (a measure of the amount of the recovered power [3]). Each operating state is related to the firing angles to be controlled.

2.3. AC/DC Load Flow Computation

A method of successive displacements is used. AC load flow and the DC load flow are executed separately and sequentially [3]. In addition, both the AC and DC load flow computations are iterative, because they are both formulated in nonlinear equations. For the AC load flow computation, the fast decoupled load flow method is used and sparsity techniques are exploited. The implemented DC load flow program deals with the following factors encountered in DC electrified railway simulation.

Two mathematical models [3], corresponding to the rectifying mode and inverting mode, are implemented for each TSS. For the rectifying mode, the model is: $V_r = V_{r0}\cos\beta_r - R_r I_r$, where V_r, V_{r0}, β_r, R_r, I_r are respectively the terminal voltage, no-load voltage, firing angle, equivalent internal resistance, and current of the rectifier. For the inverting mode, the model is: $V_i = V_{i0}\cos\beta_i - R_i I_i$, and V_i, V_{i0}, β_i, R_i, I_i are similar to those in the first model except that they refer to the inverter.

The mathematical models, corresponding to the motoring mode and the regenerative braking mode, are implemented for each train. For each operating mode, if both the train current and voltage are within their respective limits, the constant power control scheme is adopted. Otherwise, two control schemes may be used depending on the specific operating conditions. If the voltage is beyond its lower limit, which can happen in the motoring mode, the constant current control scheme will be used. On the other hand, if the voltage is beyond its upper limit, which can happen in the regenerative braking mode, the constant voltage control scheme will be used, i.e., to fix the voltage at its upper limit.

In order to enhance the computational efficiency, the "train load referral" process is used to refer all trains' consumption to their nearest TSSs or supply stations[10].

3. BICRITERION OPTIMISATION PROBLEM

As stated in section 1, the two objectives of high power recovery and even load sharing are important issues associated with the railway operation. We can come to a compromise between them by controlling the firing angles. These two objectives are conflicting, and can not reach their optima simultaneously. Thus, tradeoff must be made. One scheme [6,11] to conduct such tradeoff is to form a bicriterion optimization model that weighs these two objectives appropriately. Mathematically,

$$\text{Minimise } Obj(\overline{\beta}) = \rho \bullet Obj1(\overline{\beta}) + (1-\rho) \bullet Obj2(\overline{\beta}) \quad (1)$$

Subject to:

$$V_{Tr_j}^{\min} \le V_{Tr_j} \le V_{Tr_j}^{\max} \qquad j = 1, 2, ..., N_{Tr} \quad (2)$$

$$V_{TSS_k}^{\min} \le V_{TSS_k} \le V_{TSS_k}^{\max} \qquad k = 1, 2, ..., N_{TSS} \quad (3)$$

$$\beta_k^{\min} \le \beta_k \le \beta_k^{\max} \quad (4)$$

where

$$Obj1(\overline{\beta}) = \sum_{k=1}^{N_{TSS}} P_{TSS_k}(\overline{\beta}) \quad (5)$$

$$Obj2(\overline{\beta}) = \sum_{k=1}^{N_{TSS}} \left| P_{TSS_k}(\overline{\beta}) - \frac{\sum_{j=1}^{N_{TSS}} P_{TSS_j}(\overline{\beta})}{N_{TSS}} \right| \quad (6)$$

$$\overline{\beta} = (\beta_1, \beta_2, \dots \beta_{N_{TSS}})$$

where ρ is the objective weight, and $0 \le \rho \le 1$. V and P denote the voltage and active power, respectively. $Obj1(\overline{\beta})$ is a measure of the total power supplied to the DC railway system. $Obj2(\overline{\beta})$ is a measure of the load sharing among all TSSs. N_{Tr} and N_{TSS} are the numbers of the trains and TSSs. β_k is the firing angle of the kth TSS. Subscript "Tr_i" represents train i.

As stated above, trains are operated in two modes, i.e., the motoring mode and the regenerative braking mode. In the motoring mode, trains take power from the power system. While in the regenerative braking mode, trains send power to other trains operating in the motoring mode or back to the power system. The delivered power at each TSS depends on the operating state of the whole system, and is obtained from AC/DC load flow.

In order to ease the mathematical expression, we define the power of each TSS to be positive/ negative if it absorbs/ delivers power from/ to the power system. Thus, in order to enhance power recovery, $Obj1(\overline{\beta})$ should be minimised to ensure a maximum value for the total power recovered by all TSSs. On the other hand, for small $Obj2(\overline{\beta})$, the load sharing is uniform. Therefore, to even up the load sharing, $Obj2(\overline{\beta})$ should be minimised too. So, the composite objective function $Obj(\overline{\beta})$ should be minimised. The compromise between the recovered power and the uniform load sharing among TSSs can be dealt with by utilising a suitable optimization method for solving the above problem, and GA appears to be a powerful tool.

4. GENETIC ALGORITHM AND ITS IMPLEMENTATION

Genetic Algorithm is a search procedure for modelling the mechanism of genetic evolution and natural selection [12], which evolves solutions to a problem through selection, breeding and genetic variations. This procedure involves randomly generating a population of solutions, measuring their suitability or *fitness*, selecting the better solutions for breeding which produces a new population. The procedure is repeated to guide a highly exploitative search through a coding of a parameter space, and gradually the population evolves towards the optimal solution. GA is based on the heuristic assumptions that the best solutions will be found in regions of the parameter space containing a relatively high proportion of good solutions and that these regions can be explored by the genetic operators of *selection*, *crossover*, and *mutation*. The powerful ability of GA comes from the fact that it is robust and can deal flexibly with a wide range of problems. The main steps of the developed GA-based bicriterion optimisation program of the electrified railway are as follows:

a) **Initialization:** This is to produce a population of feasible solutions. At first, an individual is produced randomly, and its feasibility is checked with respect to the constraints. If it is feasible, the algorithm puts it into the population. The process is repeated until the number of the individuals in the population equals the specified population size.
b) **Evaluation:** This is to evaluate the fitness of each individual in the current population. Generally, the problem to be solved by GA is required to be a maximisation problem. So the objective function of equation (1), which is to be minimised, is transformed into the following form which is called the *fitness* function:

$$Fit(\overline{\beta}) = \frac{c1}{\rho \bullet Obj1(\overline{\beta}) + (1-\rho) \bullet Obj2(\overline{\beta}) + \rho \bullet c2} \tag{7}$$

where $c1$ is a specified *fitness scaling* constant that is used to map the fitness value into a preferable domain. $c2$ is a constant which is used to guarantee $Fit(\overline{\beta})$ to be positive, or to guarantee $Obj1(\overline{\beta}) + \rho \bullet c2$ to be positive.
c) **Selection:** This is a process to choose some individuals of high fitness for breeding. Many selection methods have been presented. In this work, the commonly used roulette wheel selection [12], is adopted.
d) **Recombination:** This is a process to produce new individuals from the old population. Two operators are frequently adopted for recombination, i.e., crossover and mutation. Crossover is a process which takes two given binary strings (parents) and exchanges portions of these strings to produce two new strings (children) with probability determined by the crossover rate. Each child incorporates information from the two parents. Mutation involves a change to any particular bits of an individual. Each bit is considered in turn, and is flipped from zero to one (or vice versa) with probability determined by the mutation rate.

5. TEST RESULTS AND ANALYSIS

The test system is a typical two-track (up/ down) actual system [3]. The railway line has an overall length of 19.833 km, 14 passenger stations and 7 TSSs (four of them with inverters of thyristor bridges). Each TSS is energised from a 66 kV distribution line, and supplies power to trains at a nominal DC third-rail voltage of 750 V. The trains are equipped with a continuous blending of regenerative and rheostatic braking. Some data of the study system are attached in the Appendix.

The simulation process can be conducted for many operating conditions, but only a test case is described here due to space limitations. In the test case, 7 trains are in regenerative braking and 7 trains are in motoring. Fig. 2 to Fig. 7 illustrate some of the simulation results, whose salient points are presented below.

- The relationship between the optimal controlled variables, i.e., firing angles β_k, k=1,2,3,4, and ρ is shown in Fig. 2.
- The relationships between objective 1 (the total recovered power by the 4 TSSs) and the objective weight ρ, between objective 2 and ρ, and between the recovered power of each TSS and ρ are respectively shown in Figs 3-5. Over a range of ρ = 0.9 - 1, the total recovered power of all TSSs and the recovered power by each TSS are approximately proportional to ρ, and the load sharing among TSSs is roughly inversely proportional to ρ. This is because in this ρ-range, great emphasis is placed to increase the power returned by all TSSs. When ρ=1, only the first objective is considered, and the total recovered power reaches its maximum value. In this case, a maximum of 6.2% power saving is achieved.
- Figs. 2-7 have not included simulation results for the range of ρ = 0 - 0.9. In this range, the total recovered power , the recovered power by each TSS, and the load sharing are not very sensitive with the ρ-value.
- Figs. 6&7 show the voltage performance for each train and each TSS. With no firing-angle control, train voltages have risen to a maximum value of 827.41V that is well above the design upper limit of 810V. Rheostatic braking has been activated to remove such over-voltage, and the regenerated power has not be fully recovered. When firing angles are controlled using the proposed method, all train voltages have been kept within the permitted limits between 600V and 810V for all ρ-values (Figs. 6&7). The proposed method has achieved better voltage profiles in the DC railway system.

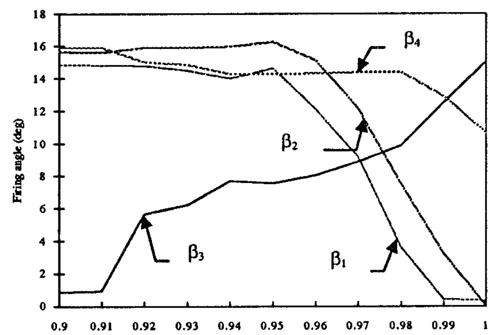

Fig. 2: Firing angle Vs ρ

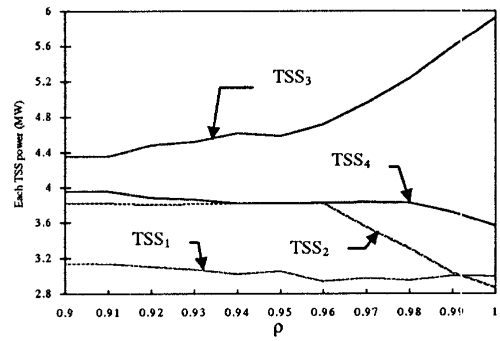

Fig. 5: Each TSS power Vs ρ

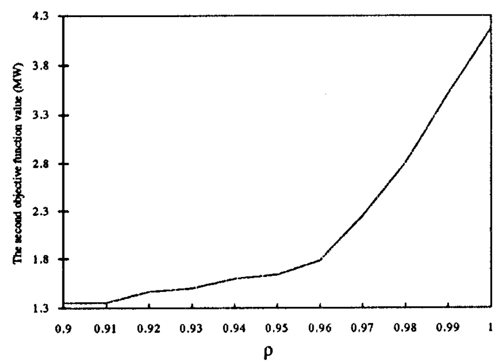

Fig. 3: The second objective function value Vs ρ

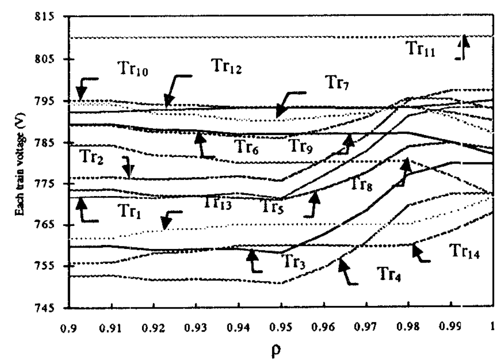

Fig. 6: Each train voltage Vs ρ

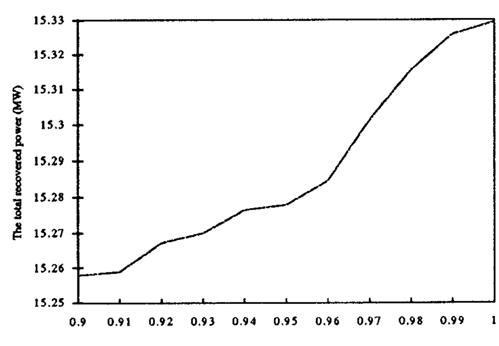

Fig 4: The total recovered power Vs ρ

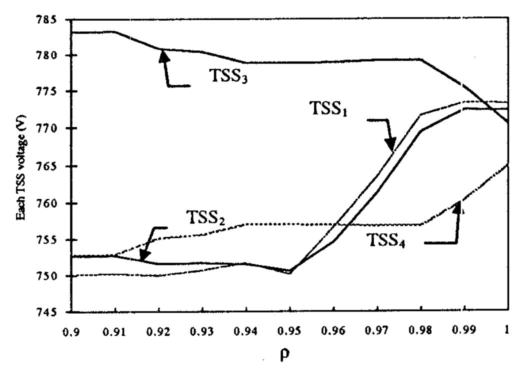

Fig. 7: Each TSS voltage Vs ρ

The test results confirm that the power recovery and load sharing can significantly be improved by controlling the firing angles using the proposed GA-based bicriterion optimisation method.

6. CONCLUSIONS

This paper has developed a bicreterion optimisation model and a genetic algorithm based method to the optimal coordination control of firing angles of traction substations. A mechanism is developed for compromising between power recovery and load sharing. With performance curves plotted with a full range of the ρ-values, a basis for making tradeoffs is formed between the two objectives. Simulation results have shown that the developed mathematical model is feasible, and the proposed GA-based method is efficient and flexible. As much as 6% of power saving can be achieved, and load sharing can greatly be improved through coordinated control of firing angles.

7. REFERENCES

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Appendix

Information about TSSs

# id	0	1	2	3	4	5	6	7	8	9
# position(m)	0	1021	2013	2806	3842	5088	6243	7704	8595	9772

# id	10	11	12	13
# position(m)	12126	13558	18485	19833

$V_{TSS_k}^{min}$ = 750V $V_{TSS_k}^{max}$ = 801V k = 1, 2, 3, 4

V_{r0} = 750V V_{i0} = 750V

R_{r0} = 0.01Ohm R_{i0} = 0.006Ohm

$V_{Tr_j}^{min}$ = 600V $V_{Tr_j}^{max}$ = 810V j = 1, 2,..., 14

Nominal track voltage: 750V

Nominal track resistance: 0.009Ohm/km