Design of Optimal Coasting Speed for MRT Systems Using ANN Models

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Abstract—The artificial neural network (ANN) has been proposed in this paper to determine the optimal coasting speed of train operation for Kaohsiung Mass Rapid Transit system (KMRT) to achieve the cost maximization of energy consumption and passenger traveling time. The train performance simulation (TPS) is applied to solve the energy consumption and the traveling time required to complete the journey between stations with various riderships to create the data set for ANN training. The ANN model for the determination of optimal coasting speed is then derived by performing the ANN training. To demonstrate the effectiveness of the proposed ANN model, the annual ridership forecast of KMRT system over the project concession period from 2007 to 2035 has been used to determine the optimal coasting speed of train sets for each study year according to the distance between stations and the passenger ridership. The power consumption profile of train sets and the traveling time of passengers have been solved by TPS simulation to verify the reduction of social cost for KMRT system operation with the optimal coasting speed derived.

Keywords- Artificial Neural Network (ANN), Mass Rapid Transit System, Optimal Coasting Speed.

I. INTRODUCTION

The mass rapid transit systems (MRT) have been implemented in many metropolitan regions to provide the public transportation function with high passenger carrying capacity to solve the problems of traffic congestion and air pollution effectively. With the increase of electricity energy cost during recent years, the energy consumption by train sets has become a very critical issue for the MRT systems to pursue higher operation efficiency. In Taiwan, the Taipei MRT System has been operated for more than 10 years with daily ridership over 1.3 million. KMRT has been constructed since 1999 and will be commissioned in early 2008. To achieve the optimization of system operation, KMRT has to design the proper coasting speed of train sets by considering the traction energy consumption and passenger traveling time. For a typical MRT system, the energy cost will contribute more than 20% of total operation cost and 75% of the total energy consumption will be consumed by train sets for propulsion purpose.

Although the energy consumption of traction drive system can be reduced significantly by operating the train sets with lower coasting speed, the traveling time to complete the journey between stations will be increased which will deteriorate the service quality [1]. To achieve the maximization of social welfare for an MRT system, the optimal coasting speed for train operation between stations should be determined by considering the cost of passenger traveling time and the cost of propulsion energy consumption of the train sets. The cost of passenger traveling time and the cost of propulsion energy consumption are determined by the ridership or number of passengers on the train set, which is varied from year to year and time to time within a daily period. An effective model should be derived to solve the optimal coasting speed for the peak and off peak operation of MRT system according to the change of ridership.

Many approaches have been presented [2, 3] to determine the optimal coasting speed of MRT train sets so that the reduction of propulsion energy consumption can be obtained. A GA-based method [4] has been proposed to synthesize the lookup table of coasting speed by which the proper locations where the operation modes of motoring, coasting and braking should be applied to minimize the energy consumption of train sets traveling between stations. Another method has been used to cope with the coasting control of MRT systems [5] by using both direct and heuristic search methods to locate the multiple coasting points for an inter-station run with the specified traveling time to maintain the system performance. In [4,5], the start coasting point and the coasting speed of a train set are determined within the specified traveling time between stations based on the decrease of energy consumption. For the operation of MRT systems, the train set starts from the station with the increase of power consumption during the acceleration stage. After reaching the coasting speed, the motoring power is switched off for energy conservation. When approaching the next station, the braking regeneration is applied so that the kinetic energy of the train set can be converted to electricity energy by induction generation. The energy consumption of the train set and the corresponding traveling time to complete the journey between stations can be simulated for different
coasting speeds. By operating the train set with the higher speed to reduce the passenger traveling time, more energy consumption will be required. Because the optimal coasting speed of MRT train operation is a nonlinear function of the unit traveling time value of passengers, the ridership and the distance between stations, the artificial neural networks are inherently suitable for the design of coasting speed for MRT systems.

In this paper, the cost of propulsion energy consumption of train sets and the cost of traveling time of passenger for all possible operation scenarios have been solved by train performance simulation (TPS) [6-8] and included in the data set for the training of ANN network. By applying the ANN model developed, the coasting speed and the speed profile of a train set operated between stations can therefore be determined according to the track alignment and passenger ridership. Up to now, ANN has been successfully used to solve the optimization problem by imitating the human neural network. It has been applied in the areas of function approximation and pattern recognition [9]. It is especially suitable for the multivariable applications because of the capability to identify the interaction between the inputs and outputs. In recent years, the ANN has been applied in the areas of load forecasting [10], harmonic prediction [11] and fault protection [12]. With the ANN model derived in this study, the optimal coasting speeds of train sets traveling between stations is determined and updated for each year according to the input neurons of annual ridership and track alignment [13, 14].

II. PROBLEM DESCRIPTION

A. Description of KMRT System

The KMRT network in Fig. 1 [15] consists of the Orange Line and Red Line with total track lengths of 42.7 km and 38 train stations. Kaohsiung City Government awarded a Build, Operate and Transfer (BOT) contract to Kaohsiung Rapid Transit Corporation with concession period of 36 years. The construction has been started since 2001 and will be commissioned early 2008. To ensure the service quality of the mass rapid transit system during the concession period, the headway of KMRT system has been determined by considering the ridership forecast in the coming years. To derive the optimal operation strategy to maximize the social welfare, the speed profile and the coasting speed for the train operation between two stations have to be solved by minimizing the total cost of traction energy consumption and passenger traveling time.

B. Mathematical model of speed profile

The propulsion traction effort and various types of operation resistance of train sets traveling between stations are calculated according to the characteristics of rolling stocks, passenger loading factor, operation mode and track alignments of the main line such as route gradient and curvature. The motion equation of train sets has been applied to find the mechanical power demand and the speed of each train set along the main line for each time snapshot of train performance simulation.

1) Train motion equation

For the operation of MRT systems, the traction effort \( F_d \) provided by induction motors will be used to generate the acceleration effort \( F \) for the train set and to overcome the operation resistance \( F_R \) [6].

\[
F = F_d - F_R = Ma
\]  

(1)

Where \( M \) is the mass of the train set and \( a \) is the acceleration. The acceleration of the train set is determined according to the operation modes in each region of speed profile, which will be used to solve the train speed by Euler’s method in Eq. (2).

\[
V_{n+1} = V_n + 3.6a\Delta T \quad \text{(km/h)}
\]  

(2)

where \( \Delta T \) is the simulation time step and \( V_n \) is the corresponding train speed for time snapshot \( n \).

The trapezoidal rule is then applied to find the new position \( S_{n+1} \) of the train set for the next time snapshot.

\[
S_{n+1} = S_n + \frac{1}{2}(V_n + V_{n+1})\frac{\Delta T}{3.6} \quad \text{(m)}
\]  

(3)

The mechanical power output of the induction motors required for the train set operation is then solved.

\[
P_{out} = F_d \times V
\]  

(4)

2) Train motion equation

The power consumption of a train set will be varied with the acceleration, the coasting, and the braking process of train operation. To simulate the power demand of an MRT system,
the accelerating propulsion power and braking regeneration power of the train set for each snapshot is solved based on the train movement simulation by considering various operation modes.

a) Acceleration stage: When the train set starts leaving the station, the operation mode of constant torque is applied until the train set reaches the speed of 22 km/h. After that, constant power mode is applied by operating the variable voltage variable frequency (VVVF) converter with quasi-six step so that the torque of the induction motors varies inversely with the speed. After the speed reaches 42 km/h, the operation mode of constant slip frequency is used with the torque of the driving motors inversely proportional to the square of the slip. The total energy consumption by the train set during the acceleration stage is then computed as the integral of propulsion power consumption.

b) Coasting stage: When the train set reaches the coasting speed, only small amount of propulsion power consumption is used to maintain the constant speed operation for the train set.

c) Deceleration stage: When the train set approaches the next station for deceleration with speed above 60 km/h, the constant power regeneration mode is used to recover the kinetic energy of train sets by braking. In this way, the variable mechanical braking power is also applied to provide sufficient deceleration for the train set without causing overloading of propulsion system. After the speed has been reduced below 60 km/h, only the electric braking is applied with constant torque mode so that full induction regeneration can be obtained. With the train speed being less than the electric brake cut off speed of 5 km/h, only the mechanical braking is applied to achieve precise train stop.

C. Speed profile simulation

To calculate the movement and the corresponding power consumption of train set along the main line of an MRT system, the train performance simulation is developed in this paper. The total weight of car body and passengers carried by the train set, the alignment of main lines such as locations of train stations, the gradient, curvature and speed restriction of main line are considered in the computer simulation. The motion equation of the train set describing the speed and time versus train location along the main line is used to derive the corresponding power consumption and speed profiles.

The train operation between stations O13-O14 of Orange Line for KMRT system, which having distance of 1035 m with the speed restriction of 64 km/h from 337 m to 525 m has been simulated. Figure 2 shows the corresponding traction effort and speed profile of the train set. The constant traction torque is applied as illustrated by the straight line from knee point 0 to 1 with the corresponding speed from zero to 40 km/h. The constant power operation mode is used for the range from knee point 1 to 2-1 with the traction effort proportional to the inverse of train speed from 40 km/h to 60 km/h. After the train speed reaches 60 km/h, the constant slip frequency mode is applied with the traction effort being inversely proportional to the square the train speed. To comply with the speed restriction, the train speed is reduced from 80 km/h to 64 km/h by applying the electric regeneration braking from location of 236 m to 337 m. The train set is then operated with cruising mode from 337 m to 525 m by consuming very small propulsion power. After that, the train is accelerated again to increase the speed from 64 km/h to 80 km/h and the coasting mode is applied from 603 m to 796 m by turning off the propulsion power. When the train approaches the next station, the electric regeneration braking is applied to achieve the energy conservation by converting the kinetic energy of the train set into electricity energy for restoration.

To verify the traction effort curve by the proposed train movement simulation, the actual traction efforts of KMRT system at the knee points have been measured in Table I. By comparing to Fig. 2, it is found that the traction efforts at the knee points solved by the computer simulation are rather consistent to the values obtained by field test.

Table II shows the traveling time and energy consumption of a train set operated between stations O13 and O14. The traveling time to complete the journey is 72.1 seconds. The propulsion energy consumption for train acceleration and the energy restoration for train regeneration have been solved as 18.64 (kWh), 9.98 (kWh) respectively.

D. Objective function

To design the optimal coasting speed of train sets operated...
between stations of KMRT system, the objective function is formulated by including the cost of energy consumption \( C_{SE} \) and the equivalent cost of passenger traveling time \( P_{SC} \) in Eq. (6). The energy consumption and the traveling time are derived by executing the train performance simulation for scenarios with different ridership and coasting speed, which will be used to form the data set for the training of proposed ANN model.

\[
F_{SW} = C_{SE} + P_{SC} \tag{6}
\]

1) **Equivalent cost of passenger traveling time**

The equivalent cost of passenger traveling time is calculated by multiplying the traveling time of all passengers to complete the journey between stations with the unit time cost [14]. By comparing to the traveling time required for the maximum coasting speed of 80 km/h, the traveling time cost of passengers at different coasting speed will be increased in Eq. (7).

\[
P_{SC} = V \ast R \ast \frac{\Delta t}{3600} \tag{7}
\]

, where \( V \) is the unit cost of passenger traveling time, \( R \) and \( \Delta t \) are the total passengers on the train set and the increase of traveling time (sec) respectively.

2) **Energy consumption cost**

The cost of energy consumption for a train set operated between stations with different coasting speed is calculated according to the reduction of energy consumption multiplied by the unit cost of energy in Eq. (8).

\[
C_{SE} = \Delta E \ast C_e \tag{8}
\]

E. **Headway of train operation**

With the growth of ridership over the study years, the headways of train operation will be reduced accordingly to meet the criterion of service quality. The loading factor (LF) of train sets and the operation headway of each transit route during the peak period is derived according to the annual ridership forecast. Figure 3 shows the headway and passenger loading of train sets operated between stations O13-O14 of the Orange Line. From the figure, the headway of train operation for the Orange line are reduced at years 2009, 2010, 2015 and 2032 with the minimum headway of 2 minutes after year 2032.

III. **DERIVATION OF THE ANN MODEL FOR OPTIMAL COASTING SPEED**

A multi-layer feed-forward neural network with back-propagation algorithm has been adopted in this study to derive the ANN model for the determination of optimal coasting speed of train sets. The data is propagated from the input layer to the hidden layers before reaching the final output layer. The error signals at the output layer are then propagated back to both the hidden layers and input layer. The sum of square error (SSE) is then minimized by adjusting the synaptic between two layers and bias in any layer during the training process of ANN models as shown in Fig. 4. For a multi-layer network, the input \( y^{k+l}(i) \) and output \( y^{k+l}(j) \) of neuron \( i \) in the \( k+l \) layer can be expressed as Eqs. (9) and (10) respectively.

\[
y^{k+l}(i) = \sum_{j=1}^{k} w^{k+l}(i,j)y^{k}(j) + b^{k+l}(i) \tag{9}
\]

\[
y^{k+l}(i) = \phi^{k+l}(y^{k+l}(i)) \tag{10}
\]

, where \( k \) is the number of outputs in the \( k \) layer, \( w^{k+l}(i,j) \), \( b^{k+l}(i) \) and \( \phi^{k+l} \) represents the synaptic weight, bias and the activation function of neuron \( i \) in the \( k+l \) layer. Because the objective function to maximize the social welfare consists of the cost of passenger traveling time and cost of propulsion energy consumption, the neuron of the input layer, \( v^{k+l}(i) \), are defined as the unit price of passenger traveling time, the ridership, and the distance between stations. The neuron of the output layer, \( y^{k+l}(i) \), is the optimal coasting speed of the train set to be determined. For an ANN network with \( K \) layers, the system equations in matrix form are given as

\[
\begin{bmatrix}
\tilde{y}^{0} \\
\tilde{y}^{k+l}
\end{bmatrix} = \begin{bmatrix}
\overline{p} \\
B^{k+l}\end{bmatrix} \tag{11}
\]

\[
B^{k+l} = \begin{bmatrix}
\begin{bmatrix}
A^{k+l} & A^{k+l} & \ldots & A^{k+l}
\end{bmatrix} & \begin{bmatrix}
B^{k+l} & B^{k+l} & \ldots & B^{k+l}
\end{bmatrix}
\end{bmatrix} 
\tag{12}
\]

, where the input signal vector \( \overline{p} \) with \( Z \) variables is expressed as \( [p(1), p(2), \ldots, p(Z)]^T \) . The input/output vector pairs \( \{[\overline{p}, \overline{\tilde{y}}],[\overline{\tilde{y}}, \overline{y}],[\overline{\tilde{y}}, \overline{\tilde{y}}],[\overline{\tilde{y}}, \overline{\tilde{y}}]\} \), which are generated by performing the train performance simulation with different scenarios of ridership and distance between stations, propulsion energy consumption, passenger traveling time and the optimal coasting speed of the train set. By representing the SSE as the performance index for the ANN network, the error function is solved as.
where, \( \bar{x}_r = \bar{y}_r - y^K_r \) is the output error and \( y^K_r \) is the final output of the \( r \)th input. To minimize the mean square error function \( E(\bar{x}) \) in Eq. (14) with respect to vector \( \bar{x} \), the Newton’s method is given by Eq. (15)

\[
E(\bar{x}) = \frac{1}{2N} \sum_{r=1}^{N} e_r^2(\bar{x}) \quad (14)
\]

\[
\Delta \bar{x} = \left[ \nabla^2 E(\bar{x}) \right]^{-1} \nabla E(\bar{x}) \quad (15)
\]

and

\[
\bar{x} = [w^1(1,1)w^1(1,2)\ldots w^1(S1,Z)b^1(1)\ldots b^1(S1)w^2(1)\ldots b^K(S1)]^T \quad (16)
\]

\[
\nabla E(\bar{x}) = J^T(\bar{x}) \nabla \bar{x} + S(\bar{x}) \quad (17)
\]

\[
\nabla^2 E(\bar{x}) = J^T(\bar{x}) J(\bar{x}) + S(\bar{x}) \quad (18)
\]

\[
N = R \times SK. \quad \text{The synaptic weights and biases are adjusted by Eq. (21)}
\]

\[
\Delta \bar{x} = -J^T(\bar{x}) J(\bar{x}) \quad (19)
\]

\[
\Delta \bar{x} = -J^T(\bar{x}) J(\bar{x}) + \mu I \quad (20)
\]

To enhance the performance of ANN training process, the Levenberg-Marquardt Back-Propagation (LMBP) algorithm [16,17] is applied in the Newton’s method as

\[
\Delta \bar{x} = -J^T(\bar{x}) J(\bar{x}) + \mu I \quad (21)
\]

where the parameter \( \mu \) is updated according to the change of the performance index for each iteration and \( I \) is the identity matrix. For the LMBP algorithm, all of the input/output vector pairs \( R \) are given to the network first, and the corresponding outputs and errors are computed by using Eqs. (11), (12) and (14). The Jacobian matrix \( J(\bar{x}) \) in Eq. (19) and the incremental change \( \Delta \bar{x} \) in Eq. (22) are calculated and the performance index is updated with the new operating point of \( \bar{x} + \Delta \bar{x} \). The ANN network becomes converged when the performance index is less than the specified tolerance. Otherwise, the parameter \( \mu \) is modified to repeat the training process of the neural network. Figure 5 shows the derivation process of proposed ANN model for KMRT system.

IV. SIMULATION RESULTS

A. Data set for ANN training

To generate the data set for the training of ANN model to solve the optimal coasting speed of train set with speed restriction, the operation of a train set between stations O13-O14 of Orange Line of KMRT has been selected for computer simulation. Figure 6 shows the increase of equivalent time cost of passenger traveling time (\( \Delta TC \)) and the decrease of energy consumption cost (\( \Delta CSE \)) when the coasting speed of the train set is reduced from 80 km/h to 65 km/h. With the decrease of coasting speed, the corresponding energy consumption of train set will be reduced while the traveling time to complete the journey will be longer to result in the larger cost of passenger traveling time. Besides, the passenger traveling time cost is increased with the increase of unit traveling time value of passengers.

Fig. 5 Derivation of ANN model for optimal coasting speed planning.

Fig. 6 Increase of passenger traveling time cost \( \Delta TC \), decrease of energy consumption cost \( \Delta CSE \) with coasting speed from 80 km/h to 65 km/h.

To generate the data set for the training of proposed ANN model, the objective function is solved by varying the unit cost of passenger traveling time with different riderships in Fig. 7. With the increase of ridership and the unit value of passenger traveling time, the optimal coasting speed is increased to achieve the best social welfare. For the unit value of passenger traveling time of NT60/h, the optimal coasting speed of 80 km/h should be applied for the train operation with the ridership of more than 423 passengers. Also, same optimal
coasting speed of 71 km/h should be considered for the ridership between 335 passengers and 364 passengers with the unit value of passenger traveling time of NT35/h because the value of objective function resulted remains the same.

Fig. 7 The relationship of optimal coasting speed and ridership with different values of passenger traveling time.

B. Design of optimal coasting speed

By performing the training of neural network with the back propagation process, the ANN model for the design of optimal coasting speed has been derived in this paper. The optimal coasting speed for the Orange Line of KMRT system during the concession period of BOT project has been obtained by considering the unit value of passenger traveling time, the ridership and the propulsion energy consumption. To demonstrate the effectiveness of the proposed methodology to determine the optimal coasting speed of MRT system, the line section between stations O13 and O14 of Orange Line has been selected for computer simulation. The ridership and operation headway have been determined according to the ridership forecast and the service criterion of KMRT system. For the operation of train sets during peak period, the optimal coasting speed of KMRT system has been solved as shown in Fig. 8. It is found that the headway is reduced with the growth of ridership at the specific years to comply with the service criterion and the optimal coasting speed for each study year is varied with the change of passenger ridership. The optimal coasting speed of train sets is increased with the increase of unit value of passenger traveling time although the propulsion energy consumption will be increased too.

To illustrate the cost reduction for the KMRT system by adopting the proposed coasting speed, Fig. 9 shows the reduction of energy consumption cost and the increase of passenger traveling time cost for the operation of train sets between O13-O14 over the study years. The traveling time to complete the journey with the optimal coasting speed will be longer as compared to the train operation with the maximum coasting speed of 80 km/h. For year 2019, the cost of energy consumption has been reduced by NT3.9M while the cost of passenger traveling time is increased by NT2.0M for train operation between O13 and O14. The net cost reduction of NT1.9M has therefore been obtained. It is estimated that the social welfare will be increased by NT49M over the concession period for the train operation between O13 and O14 with the optimal coasting speed solved by the proposed ANN model. For the final year of concession period, 2035, the optimal coasting speeds of the train sets operated between two stations have been solved as show in Fig. 10. It is found that the maximum operation speed 80 km/h should be applied for the journey of O7-O8 because of the heavy ridership while the coasting speed of 65 km/h is used for the journey of O4-O5 because of the light ridership and shorter distance between stations. With the expected increase of electricity charge by Taipower in the future years, the slower coasting speed will be considered for more reduction of the energy consumption by KMRT system.

Fig. 8 The optimal coasting speed and ridership of train set for O13-O14.

Fig. 9 The increase of energy consumption cost, the traveling time cost of passengers and the reduction of social cost for the train operation between O13 and O14 with the optimal coasting speed proposed.

Fig. 10 The optimal coasting speed of train set for the Orange Line during peak period.
V. CONCLUSION

In this paper, an artificial neural network (ANN) model has been derived to determine the optimal coasting speed of train operation for Kaohsiung Mass Rapid Transit System to achieve the maximization of social welfare. The objective function is formulated by considering the cost of propulsion energy consumption of train sets and the traveling time cost of passengers. The energy consumption and the traveling time to complete the journey with different riderships and distances between stations have been calculated by train performance simulation to generate the data set for the training of ANN network. By considering the variations of traveling time values of passengers, the energy charge rate, the ridership of train sets and the distance between stations, the optimal coasting speed of train sets is derived by the ANN model derived in a very efficient way.

To demonstrate the effectiveness of the proposed ANN model to solve the optimal coasting speed of train sets, the Orange Line of KMRT system has been selected for computer simulation. By applying the ANN model derived, the optimal coasting speeds of train operation have been determined according to the distance between stations, the annual ridership over the study years. Although the traveling time cost of passengers to complete the journey is increased after adopting the optimal coasting speed, the reduction of energy consumption cost resulted will be more significant and economically justified. With the dynamic variation of passenger ridership for the daily MRT operation, the ANN model derived can be used to support the adjustment of coasting speed for train operation to enhance the operation efficiency of MRT systems. It is concluded that the ANN model derived does provide an important tool for the design of proper operation strategy to achieve the maximization of social welfare for the operation of MRT systems.

REFERENCES


