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MODELS FOR ESTIMATING ENERGY CONSUMPTION OF ELECTRIC TRAINS

Jyh-Cherng JONG
Ph. D., P.E., Research Scientist
Civil, Hydraulics and Informatics Research Center
Sinotech Engineering Consultants, Inc.
171 Nanking E. RD. Sec. 5,
Taipei 105, Taiwan(R.O.C.)
Fax:+886-2-2765 5010
E-Mail:jcjong@sinotech.org.tw

En-Fu CHANG
Research Scientist
Civil, Hydraulics and Informatics Research Center
Sinotech Engineering Consultants, Inc.
171 Nanking E. RD. Sec. 5,
Taipei 105, Taiwan(R.O.C.)
Fax:+886-2-2765 5010
E-Mail:efchang@sinotech.org.tw

Abstract: Railway operators are heavy users of electric energy. To implement energy saving programs and to study economical operation strategies, an energy estimating model is required. In this paper, two models for estimating energy consumption of single train operation are presented. To verify the proposed models, a real railway link and an electric train from Taiwan Railway Administration (TRA) are selected for the experiment. The energy consumption estimated from the proposed model is then compared with that estimated by other commercial software. It is found that the difference is only 0.22%, demonstrating that the proposed models are accurate enough in practice for estimating energy consumption. The models can be further extended to develop models and algorithms for estimating power demand of multiple-train operation and minimizing energy consumption through different driving strategies.

Key Words: Energy Consumption, Train Performance Simulator, Optimal Driving Strategy

1. INTRODUCTION

Energy resources are quite scarce in many countries. One of the most important energy resources is electricity. In the last few years, Taiwan has suffered from electricity shortage problem in summer. For this reason, the government has encouraged all public and private sectors to reduce electricity consumption.

Railway operators are heavy users of electricity resource with the increasing use of electric trains. The water and power charge of Taiwan Railway Administration (TRA) has increased from 12.92% of total operating expense in 1998 to 13.32% in 2002. Similar situations can also be found in other countries. To implement energy cost reduction programs and study economical train operation strategies, a precise energy model for estimating train electricity consumption is required. In this paper, two models for estimating single train energy consumption are presented. Both require detailed train running states outputted from train performance simulator (TPS) or speed profile generator, including train velocity, running time, corresponding tractive effort and braking force. The first model estimates voltage and current usages via train velocity, and then computes electric power. The second model estimates electric power through train velocity, corresponding tractive effort and energy efficiency curve. Both models employ numerical integration method to estimate the overall energy consumption of a single train operation. Although the underlying concepts of the two models in calculating electric power are different, it is found that the first model is a special case of the second one from mathematical point of view. A mechanism is thus developed in this paper to convert voltage and current curve into a single efficiency curve that can be used in the second model. In addition, an error reduction algorithm is also developed to reduce the error in numerical integration for estimating energy consumption.

To verify the proposed models, a real railway link and an electric train from TRA are selected as the test case. The energy consumption estimated from the proposed model is compared with other commercial software. At the end of this study, the effects of traction ratio and minimal allowable coasting speed on energy consumption are also analyzed. The proposed models can be further extended to develop models and algorithms for estimating power demand of multiple-train operation and minimizing energy consumption through different driving strategies.

2. LITERATURE REVIEW

Energy saving is always an issue that draws much attention from rail authority. Previous researches and demonstrations have confirmed that energy consumption can be reduced through appropriate operation strategies. In Paul's study (Paul, 1999), 5% extension on run time can produce energy savings up to 20% on a suburban system. Tomii (2003) develops a model which estimates power consumption at high precision with 2% deviation from real situation. It is found that reducing maximum speed and tactfully performing coasting can reduce energy consumption about 7% ~ 20%.

TMG International Consultants proposes an optimal train performance simulator which gains a 13.7% reduction in traction energy consumption by the timetable optimization process without increase in running time. The simulator shows a reduction in traction energy consumption from 576 kWh per unit to 497 kWh per unit as a result of the timetable optimization process.

In order to study energy saving problems, an accurate energy estimation model is necessary. As early as in 1985, Majumdar proposes four main stages of train movement including (1) acceleration, (2) balancing, (3) coasting, and (4) deceleration. Equation (1) is the summary of his ideas for calculating energy consumption. It shows that the total energy consumed in train operations is the product of force and displacement. Coefficients in the equation are energy efficiency and factors for converting the work done in ton-km into electric power units. Majumdar also proposes a statistical method for estimating energy. However, this approach is an actual measurement and thus, contributes less functions in energy saving.

$$W_T = \left[\frac{2.725}{0.814}\left(\sum T_A \times d_A + \sum T_B \times d_B\right)\right] + \left[\frac{P_a}{0.964} \times \left(\frac{\sum d_C}{v_C} + \frac{\sum d_D}{v_D}\right)\right] \tag{1}$$

where W_T =total power energy consumption (kWh)
T =force in tones due to tractive effort (ton)
d =distance traveled in km at that speed range (km)
P_a =power consumption by all auxiliaries (kWh)
A, B, C, D = Acceleration, Balancing, Coasting and Deceleration stage, respectively

Goodman (1987) develops single train and multi train simulation programs. The voltage received by a train will vary with position and the simultaneous action of other trains in multi train model, while it remains a constant in single train model. This is the main difference between two models in estimating energy consumption. Goodman considers detailed factors in his model, including substation, feeder cable and volt-drop, etc.

Recently, Caputo (2000) develops a model that considers not only power supply parameters, but also energy storage devices, such as accumulator, flywheels or capacitors. The expected benefits of the energy storage devices are the reduction in energy consumption as well as line peak loads. This becomes a new trend in saving electric energy for train operations.

Estimation of energy consumption can be categorized mainly into electric-power approach and kinematics approach. Generally, the electric-power method calculates electric energy that is directly imported into the train. The kinematics method estimate energy consumption via kinetic energy and efficiency factor. The two models are explained more detailed in the following subsections.

2.1 Electric-Power Based Model

Wardrop (1989) proposes an electric-power based model to estimate energy consumption. The basic calculation, as shown in equation (2), requires line voltage, current and motor combination code, etc. The k value is the number of parallel motor circuits. According to equation (2), this method contains an assumption that energy consumption has a linear relationship with the proportion between actual traction and maximum traction. Eash (1978) and Lee (2000) also use this approach in their models, but each uses different concept to determine voltage or current.

$$E_m = \int \frac{1}{1000 \times 3600} \times V \times I_m \times k \times r_T dt = \frac{1}{3.6 \times 10^6} \times k \times V \int I_m \times r_T dt \tag{2}$$

where E_m=main power energy consumption (kWh)

V=voltage (V)

I_m=motor current (A)

k=motor combination code, $k \geqq 1$

$r_T = \frac{T_{actual}}{T_{\max}}$, the proportion between actual traction T_{actual} and maximum traction $T_{\max}$,

$0 \leqq r_T \leqq 1$

t=operation time (s)

2.2 Kinematics Based Model

As shown in Figure 1, after electric power inputs to rolling stocks, it will go through converter, motor, and mechanic devices to output traction power for train movements. The entire procedure involves more or less energy loss. The motor efficiency is defines as the division of P_{out} over P_{in}. In equation (3), motor efficiency, train traction, and speed are inputs for estimating input power. Energy consumption is estimated via equation (4).

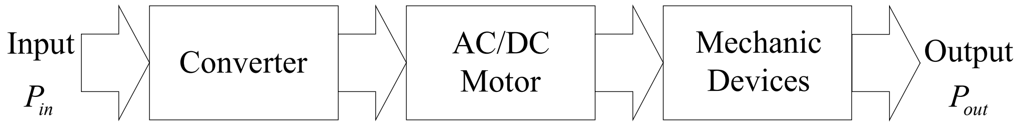


Figure 1 Energy Consumption Sketch Map

$$\eta = \frac{P_{out}}{P_{in}} = \frac{0.2\overline{7} \times T \times v}{P_{in}} \tag{3}$$

$$E_m = \int P_{in} dt \tag{4}$$

where η =motor efficiency, $0<\eta\leq 1$
P_{out} =output power (kW)
P_{in} =Input power (kW)
T =tractive effort (kN)
v =train velocity (km/h)

Uher (1987a, 1987b) develops EMM (Energy Management Model) and TOM (Train Operations Model) which use above approach. Piotr (2001) presents a model on MATLAB environment. His study also utilizes kinematics based model. In addition, special attention is given to wheel slippage. Coefficients measured from real data are considered in his study to develop a customized model for SJ RC4 locomotive.

2.3 Summary

According to the above literature, estimation of energy consumption for electric trains is widely applied to the planning/design of power supply systems and the study of optimal driving strategies. Research on optimal driving strategies requires higher precision than power system planning/design since the latter usually takes the worst case to consider safe margins. Note that both kinematics based and electric-power based models are broadly adopted to develop computer software. Although they are derived from different viewpoints, their accuracies are acceptable if suitable data are correctly inputted to the models.

In early days, the developing tool of computer models for estimating train energy consumption is usually FORTRAN language. For the past few years, C++ language has replaced FORTRAN gradually. Some researches build energy model under applications like MATLAB. Although this solution seems convenient, the main disadvantages are computationally inefficiency and non-portable executable files.

3. SIMULATION MODEL

As described in the previous section, the computation of energy consumption requires the integration of input power over time, no matter which model is applied. Since the power does not have specific function form, the integration is usually solved numerically. In train simulation programs, the estimation of energy consumption is usually based on train movement module. In order to obtain the parameters for calculating energy consumption at every time step, a train dynamic model is required.

A complete energy estimation model for electric trains includes at least three parts, i.e., the energy used by the traction motors, the energy consumption of auxiliary equipments, and the energy produced by regenerative braking. These three modules are introduced in the following sections:

3.1 Energy Model for Traction Motors

The energy consumed by traction motors is utilized to produce sufficient tractive effort for train movements. It is the majority of total energy consumption of electric trains. In the proposed model, the kinematics based approach is selected to estimate energy consumption. The reason is that the input data of electric-power based model implies the concept of motor efficiency. Through suitable transformation, the input of electric-power model can be converted into a single efficiency curve. Section 3.4 will explain the mechanism in more detailed.

According to Equation (3), (4), energy consumption is calculated from train traction, speed, and motor efficiency at every time step. These variables are obtained from train performance simulator or speed profile generator except motor efficiency. Usually, motor efficiency is a function of tractive effort and velocity as shown in equation (5). An example measured from empirical data of Taipei Metro EMU is plotted in Figure 2. There are corresponding efficiency curves for different tractive efforts. It is possible that these efficiency curves intersect each other. After twice interpolations, efficiency value for a specific traction and velocity can be acquired. Whenever the tractive effort or velocity cannot be covered by the curves, boundary value is adopted instead of extrapolation to avoid unreasonable efficiency.

$$\eta = f(T, v) \tag{5}$$

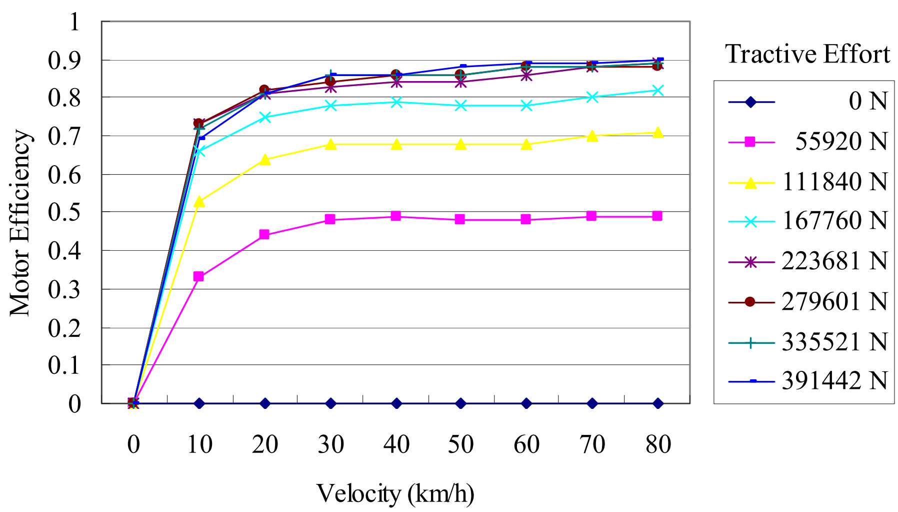


Figure 2 Motor Efficiency Curves for Taipei Metro EMU

3.2 Energy Model for Auxiliary Equipments

Auxiliary equipments include lighting, air conditioning, etc. In general, their energy consumption rate is considered as a constant. Assume that auxiliary equipments work all the time in the simulation. Then the power consumption can be calculated by

$$E_a = \frac{P_a \times t_a}{3600} = \frac{(P_{am} \times n_m + P_{at} \times n_t) \times t_a}{3600} \tag{6}$$

where E_a =total energy consumption for auxiliary equipment (kWh)
P_a =total electric power for auxiliary equipment (kW)
t_a =train operating time (sec)
P_{am} =electric power per locomotive car (kW)
n_m =number of locomotive cars.
P_{at} =electric power per trailer cars (kW)
n_t =number of trailer car.

3.3 Energy Model for Regenerative Braking

Modern electric trains are usually equipped with regenerative braking. During braking period, electric power is generated from kinetic energy of the train. Note that the braking force of the train is composed of friction braking force and motor braking force. Only the latter can be used to produce electricity. Thus, equation (7) must be applied to determine the electric braking force first. Then the product of the motor braking force, velocity and regenerative efficiency yields the electric power produced by the regenerative braking, as expressed in equation (8).

$$B_T = B_e + B_f \tag{7}$$

$$P_r = \frac{1}{3.6} \times B_e \times v \times \eta_B \tag{8}$$

Where B_T =total braking force (kN)
B_e = electrical (regenerative) braking force (kN)
B_f = friction breaking force (kN)
η_B = regenerative system efficiency
P_r =electric power of regenerative braking (kW)

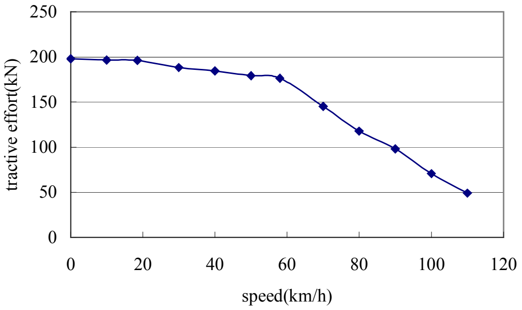
The logic behind the model is similar to the energy model for traction motors. However, this model is only optional since not all electric trains equipped with regenerative braking. Moreover, the power energy produced by regenerative braking is not utilized by the train itself unless it is equipped with energy storage devices, like accumulator or capacitors.

3.4 Transformation of Input Data

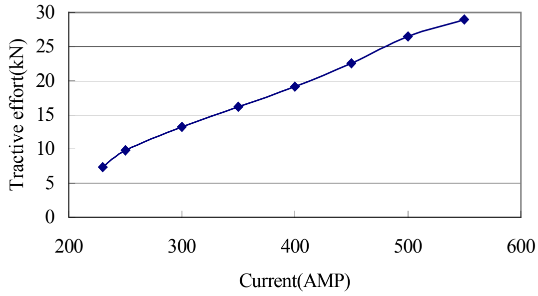
As mentioned in section 2.2, motor efficiency is defined as the ratio of output power to input power. If only the input data for electric-power based model is available, then the efficiency curve for kinematics based model can be derived from the following equation:

$$\eta = f(T, v) = \frac{P_{out}}{P_{in}} = \frac{(T \times v)/3.6}{(k \times V \times I_M \times \frac{T}{T_{\max,v}})/1000} = \frac{v \times 1000 \times T_{\max,v}}{3.6 \times k \times V \times I_M} \tag{9}$$

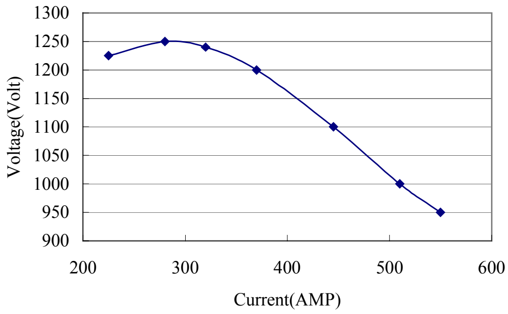
For example, Figure 3 (a) ~ (c) are the motor characteristics of E200 electric locomotive from TRA. Following equation (9), these figures can be converted into Figure 3 (d), which can be further used in kinematics based model. Thus, the electric-power based method can be considered as a special case of the kinematics based model from mathematic point of view.



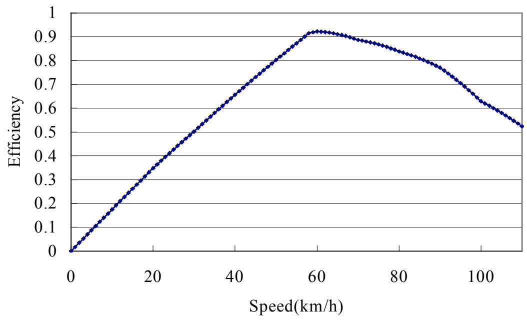
(a) Traction-Velocity Curve



(b) Traction-Current Curve



(c) Voltage-Current Curve



(d) Efficiency Curve

Figure 3 The Input (a~c) & Output (d) for Data Transformation

There are several advantages for the data transformation. First, the energy consumption estimated from the kinematics based model is exactly the same as that from the electric-power based model. Second, the energy models for traction motor and for regenerative braking are both estimated from efficiency curve and have the same input format. Third, it will be easier to check whether the efficiency curve is reasonable since it must fall in between 0 and 1. Finally, it provides very useful information for studying optimal driving strategies.

3.5 Error Reduction Algorithm

The proposed model requires detailed train information at each time step, including tractive effort, braking force, velocity, etc. These data can be obtained from TPS or speed profile generators. The energy consumption is then estimated by numerical integration. As a result, the error is dependent on the interval of time step. A high precision can be expected if the time increment is very small. But this would increase computation time. Note that the error is not originated from the interval of time step, but also due to fixed tractive effort and velocity in estimating energy consumption at each computation cycle. It is possible, however, to reduce the error without decreasing time interval. This section introduces such an error reduction algorithm.

Let T denote tractive effort (or braking force) and v be the velocity of the train. For any two successive states (T_n, v_n) and (T_{n+1}, v_{n+1}), the average velocity (i.e., $(v_1 + v_2)/2$) can be used to estimate energy consumption instead of v_n and v_{n+1}. However, the adjustment of T is a little complex since it may be positive (traction) or negative (braking). There are nine combinations of T_n and T_{n+1} (see Table 1), which can be further classified into five situations. The adjustment of T in calculating energy consumption is discussed as follows:

Table 1 Combinations between T_n & T_{n+1} and Their Corresponding Situations

T_n \ T_{n+1}	T_{n+1}>0	T_{n+1}=0	T_{n+1}<0
T_n>0	I	II	II
T_n=0	III	III	III
T_n<0	IV	IV	V

1. Situation I: This situation happens frequently in the whole simulation. Traction shall use the average of T_n and T_{n+1}.
2. Situation II: This situation indicates that train uses traction T_n continuously until the next running state. So we can estimate energy consumption by T_n.
3. Situation III: There is no energy consumption in this situation.
4. Situation IV: There is no energy consumption in this situation either. But regenerative energy must be estimated with T_n.
5. Situation V: The average of T_n and T_{n+1} is used to estimate regenerative energy in this situation.

Note that this proposed algorithm still has its limitation for error reduction due to time interval. If accuracy is a major concern, a smaller increment is suggested.

4. CASE STUDY

In order to demonstrate the proposed model for estimating energy consumption of electric trains, a real rail link and an electric train from TRA are selected for the case study. The rail link is Taichung line, which consists of 17 stations and is about 85 km long. The electric train is made up by E200 electric locomotive and 15 passenger cars. The locomotive is equipped with 6 parallel DC motors without regenerative braking.

As mentioned before, the estimation of energy consumption requires detailed train dynamics. These data is resulted from a train simulator "TrainSim" developed in Jong and Chang (forthcoming). The input data, simulation result, and sensitivity analysis for the case study are discussed in the following subsections:

4.1 Input Data

There are lots of input parameters for the simulation, including train properties, speed regulation rules, railway alignment, operation parameters, stopping patterns, etc. The major input data of the train is listed in Table 2. Tractive effort and motor efficiency curves are displayed in Figure 3 (a) and Figure 3 (d), respectively. The railway data includes station, grade, curve radius, the tunnel type. The operation parameters consist of origin and destination stations, dwell plans, coasting strategies, etc. In this case study, the dwell time are set to 60 seconds at all stations except Taichung station whose dwell time is 120 seconds due to heavy passenger flow. The parameter of simulation time interval is set to 0.5 seconds in this case study.

Table 2 Major Characteristics of the test train

	Locomotive car	Trailer car
Number	1	15
Light Weight/Full Weight (ton)	96 ton/96 ton	30 ton/35 ton
Car Length (m)	17.1 m	20 m
Speed Limit (km/h)	110km/h	100km/h
Running Resistance Coefficient(‰)	$2.594+0.0067\times V+0.3934\times\frac{V^2}{W}$	$1.24+0.0069\times V+0.000313\times V^2$
Starting Resistance Coefficient(‰)	5‰	3‰

4.2 Simulation Result

Table 3 shows the energy consumption of shortest time and proper time operation strategies. The proper operation time is estimated from the speed profile that is generated in a way to mimic TRA experts in preparing speed profiles. It is found that the shortest time operation consumes more energy but reduces journey time. Because the downward direction of Taichung line has more downgrade sections, the downward operation consumes less energy than upward direction in either one of the operation strategies.

Table 3 Energy Consumption Results

	Shortest Time Operation	Proper Time Operation
Chu-nan to Chang-hua (downward)	2276.82 kWh / 96.52 min	1922.66 kWh / 106.67 min
Chang-hua to Chu-nan (upward)	2348.32 kWh / 95.78 min	2020.93 kWh / 105.28 min

Since the real energy consumption is not available, the result obtained from the proposed model is compared with the statistical report of TRA. In recent 5 years (1998 ~ 2002), the average energy consumption rate for all rail railway lines and all electric locomotives is about 3.44 kWh/100 ton-km, whereas the consumption rate calculated from the proposed model is 3.62 kWh/100 ton-km for downward operation and 3.80 kWh/100 ton-km for upward operation, under proper time operation strategies. The results are quite consistent.

4.3 Sensitivity Analysis

The factors that affect energy consumption are very complicated. Several factors including traction ratio, loading coefficient, minimal allowable coasting speed and train speed limit are selected for sensitivity analysis. It is found that each of the factors influences energy consumption significantly and energy consumption always trades off with running time. For real applications, rail authority usually looks for minimum energy consumption under a specific running time. Among these factors, traction ratio is one of the popular control options for optimal driving strategy. Its sensitivity analysis shows that energy consumption is a convex function (U shape) of traction ratio, and the optimal traction ratio to drive the train is around 0.82, as shown in Figure 4.

Because traction ratio is the most important factor that affects energy consumption, the joint effects of traction ratio and other factors on energy consumption are analyzed. In Figure 5, the x-axis, y-axis and z-axis represent loading factor, traction ratio and energy consumption, respectively. It is found that for high loading factors, the effect of traction ratio on energy consumption is more significant. When traction ratio is small, the energy consumption is very sensitive to loading factor.

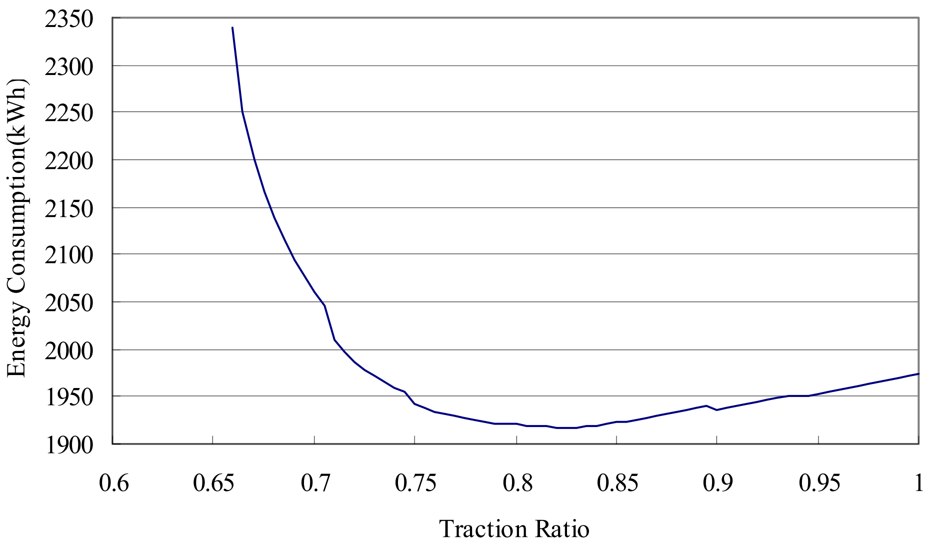


Figure 4 Sensitivity Analysis of Traction Ratio

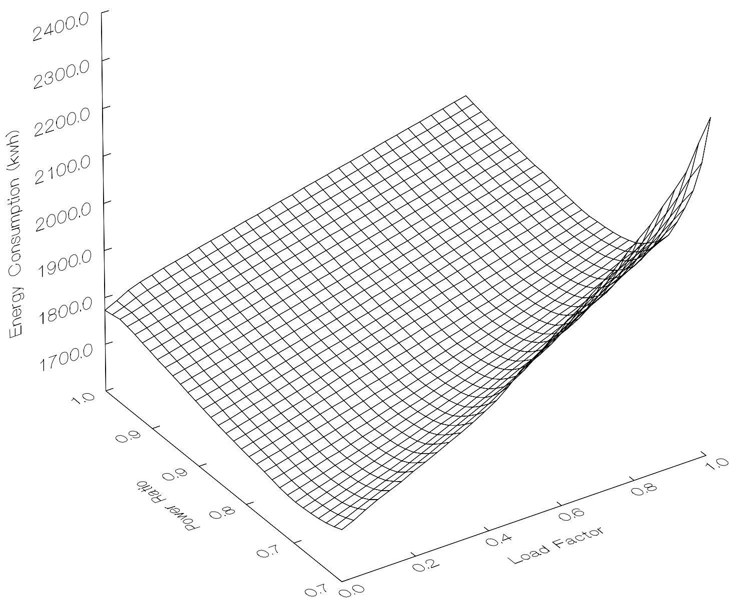


Figure 5 Relationship between Traction ratio, Loading Factor, and Energy Consumption

The speed limit also has great impacts on energy consumption. Figure 6 shows that energy consumption decreases as the reduction of maximal train speed increases up to 40 km/h. After that, the energy consumption increases gradually. Figure 6 implies that a settle point exists in the middle of the surface.

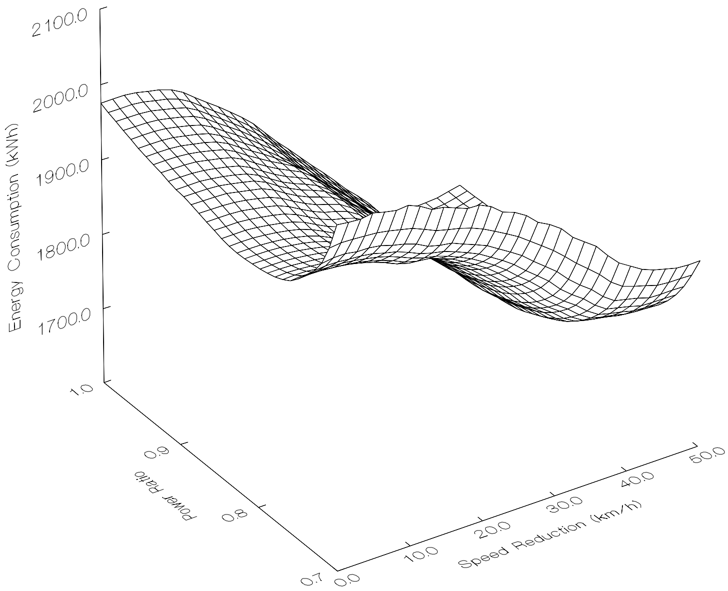


Figure 6 Relationship between Traction Ratio, Speed Limit Reduction, and Energy Consumption

Figure 7 shows the joint effect of minimal allowable coasting speed and traction ratio on energy consumption. It is found that energy consumption decreases as allowable coasting speed decreases, and energy savings is insignificant for allowable speed lower than 30 km/h. The energy consumption looks like a convex function of traction ratio and minimal allowable coasting speed.

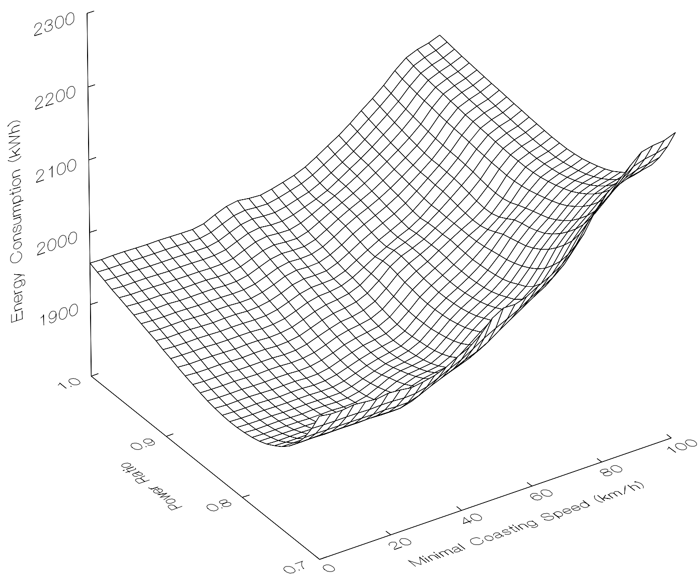


Figure 7 Relationship between Traction Ratio, Minimal Allowable Coasting Speed, and Energy Consumption

5. MODEL VERIFICATION AND VALIDATION

The most accurate method for model verification and validation is to compare the real energy consumption data with that estimated from models under the same conditions. However, the measurement of energy consumption in real operation is difficult. In addition, train operation pattern significantly differs from driver to driver, which causes remarkable differences in the energy consumption. For these reasons, the proposed model is verified by comparing the results with other commercial software. The one adopted in this study is TOM (Train Operation Model) developed in Uher and Disk (1987), and Uher (1987). TOM has been applied in many projects, including Washington Metro, Metropolitan Atlanta and Baltimore Metro, etc. The largest difference was less than 10%.

5.1 Modification of Input Data to TrainSim

There are many differences in input format and calculation logic between models. TrainSim take account of some practice rules in TRA that TOM model does not consider. In order to make a fair and reasonable comparison, the input data for TrainSim must be properly modified to comply with the input of TOM. The modifications are explained as follows:

1. Neutral Section Effect: When an electric train passes through a neutral section, the power must be cut off to prevent pantograph sparkle. Because TOM does not consider this effect, the option in TrainSim is disabled.
2. Starting Resistance: After a train starts to acceleration and before it runs up to a certain speed, extra resistance is acting on the train in addition to running resistance. The TRA experience shows that starting resistance coefficient ranges from 5~10‰. The resistance is set to zero in TrainSim since TOM does not take this parameter.
3. Curve Resistance: TrainSim has an interface for inputting curve resistance, but TOM uses a fixed coefficient (0.8 lbs/ton/degree of curvature). Thus, the curve resistance input to TrainSim is set to the same value in TOM.
4. Tunnel Resistance: In this case study, there are 5 tunnels with total length longer than 9 km. When a train runs into a tunnel, extra resistance is imposed on the train due to piston effect. Since TOM does not consider tunnel resistance, the parameter in TrainSim is set to zero.
5. Simulation Point: TrainSim can simulate speed profiles based on the head, middle, or tail of the train. The option of head is selected to be consistent with TOM.
6. Operation Objective: TrainSim provides option for selecting shortest or proper time operation. The option for proper time operation is not provided in TOM. Thus, both models estimate energy consumption under the strategy of shortest time operation.

5.2 Comparisons of Results

Table 4 shows the energy consumption estimated from TOM and TrainSim for each section, as well as the difference between them. It is found that the results are quite close. The difference between the two models ranges from -0.23% to 1.59%. The largest difference (1.59%) happens in “Nan-shih to Tung-lo” section. The absolute error is about 0.31% on average, and the overall difference for the entire operation is only 0.22%. Note that the error is not completely ascribed to the proposed energy model. In fact, the estimated operation time from TrainSim is slightly different from TOM. The difference in journey time is about 0.16%

(Jong and Chang, forthcoming in 2005). The results demonstrate that the proposed model is accurate enough for estimating energy consumption.

Table 4 Comparisons of Energy Consumption between TOM and TrainSim

	Distance	TOM Estimate	TrainSim Estimate	Difference
Chu-nan to Tsao-chiao	5.372 km	228.75 kWh	230.19 kWh	0.63%
Tsao-chiao to Feng-fu	6.346 km	264.40 kWh	265.50 kWh	0.42%
Feng-fu to Miao-li	3.493 km	201.89 kWh	201.89 kWh	0.00%
Miao-li to Nan-shih	6.662 km	419.11 kWh	419.24 kWh	0.03%
Nan-shih to Tung-lo	4.147 km	174.89 kWh	177.67 kWh	1.59%
Tung-lo to Say-yi	7.447 km	426.60 kWh	426.77 kWh	0.04%
Say-yi to Tai-an	10.862 km	290.81 kWh	290.74 kWh	-0.02%
Tai-an to Hou-li	2.609 km	183.73 kWh	183.65 kWh	-0.04%
Hou-li to Feng-yuan	6.785 km	227.26 kWh	229.05 kWh	0.79%
Feng-yuan to Tan-tse	5.022 km	155.17 kWh	155.69 kWh	0.34%
Tan-tse to Tau-yuan	5.242 km	156.13 kWh	156.31 kWh	0.12%
Tau-yuan to Taichung	3.916 km	144.25 kWh	144.30 kWh	0.03%
Taichung to Da-cing	4.284 km	154.13 kWh	154.45 kWh	0.21%
Da-cing to Wu-jih	2.922 km	135.53 kWh	135.22 kWh	-0.23%
Wu-jih to Cheng-kung	3.352 km	175.67 kWh	175.22 kWh	-0.26%
Cheng-kung to Chang-hua	7.075 km	229.36 kWh	229.69 kWh	0.14%
Total	85.536 km	3567.67 kWh	3575.58 kWh	0.22%

6. CONCLUSION AND RECOMANDATIONS

The primary objective of the study is to build a simulation model for estimating the energy consumption of electric trains. The proposed model integrates two methods found in the literature by converting the input data. To increase the precision of the result, an error reduction algorithm is also introduced in this paper. The model is finally verified with commercial software. The results are consistent and the overall error is only 0.22%.

The proposed model requires detailed train dynamics for estimating energy consumption. Therefore, any factors influencing train operation also affect the results. Some of them are inflexible for operations. For instance, loading factor and dwell plan are dependent on rider ship and passenger flow that cannot be determined by the operator. On the other hand, some factors can be regarded as control variables, for example, traction ratio, minimal coasting speed, reduction in train speed limit, etc. Through properly control, it is possible to reduce energy consumption to trade off with running time. It is recommended that a systematic driver command model should be developed to solve this optimization problem.

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