Estimating efficient value of controllable variable using an adaptive neural network algorithm: Case of a railway system

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This study proposes a method, using adaptive neural network (ANN), to predict, estimate and evaluate performance variables without requiring any restrictive assumptions, taking case of a railway system. Also, by means of this method, it would be possible to compare actual performance data with estimated values and route their assignable causes in future periods. Energy consumption norm of vehicles in case of energy railway and real data of energy consumption in Iranian railway is considered.

Keywords: Adaptive neural network (ANN), Decision making units (DMUs), Railway system

Introduction

Rail transportation plays an important role in the economic development of a country. Normally, energy consumption does not clearly distinguish whether energy is spent for passenger transport or freight transport. Linear programming approaches as Data Envelopment Analysis (DEA) estimate energy based on passenger and freight performance1. Hilmola2 used DEA to reveal efficiency development in railway freight sector and observed that a small number of countries have only been able to improve their efficiency performance during the past decade. A fuzzy dynamic multi-objective DEA model has been proposed3 to improve discriminating power of DEA. Karlaftis4 has studied ownership and competition in European transit for assessing efficiency by using dynamic ARCH error structure. Lan & Lin5 proposed 4-stage DEA to assess 44 worldwide railways over 7 years (1995-2001) with environmental effects, data noise and slacks. Yu6 employed traditional data development analysis and network data development analysis to study efficiency of 40 global railways. Adaptive neural networks (ANN) can be useful for non-linear process that has an unknown functional form7. In empirical field, ANNs showed comparability or superiority to conventional methods for estimating functions8,9. Also, in railway industry, most studies10-13 utilized historical and existence data only for analyzing past performance.

This study proposes an algorithm based on general ANNs for predicting input variables in time series and estimating production function in regression structure. Input variables are predicted by ANN, and then result values are used to estimate and predict efficient value of controllable variable (output).

Experimental Section

Parametric efficiency frontier analysis method based on ANN technique was used for predicting efficient energy in Iran Railway industry for 1996-2005, without requiring any restrictive assumptions.

Proposed Algorithm

At first, input variables of next period are predicted by two distinct ANN-TS and then fed to ANN-R for estimating controllable variable (output). Proposed computational method is able to find a stochastic frontier based on estimated values of controllable variable without explicit assumptions on functional structure of stochastic frontier. By obtained values of stochastic frontier, efficient value for controllable variable for next period is determined. In proposed algorithm, following steps are used:

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**Step 1**
Determination of input(s) and output (P) variables under input oriented (IO) assumption [input (C) and output(s) variables under output oriented (OO) assumption] of the model.

**Step 2**
Collect data set S in all available previous periods, which describe input-output relationship for decision making units (DMUs). Assuming that to estimate the value of P under IO assumption (C values under OO assumption) such that future period have the best efficiency with respect to n-1 last periods. In this manner, each of the n-1 previous period and also the future period can be assumed as a DMU and so there are n DMUs to be evaluated. Inputs under IO assumption (P values under OO assumption) should be estimated by means of time series regression. To predict time series process in original proposed algorithm, this sub-algorithm is proposed. ANN is used for time series process estimation and forecasting in proposed sub-algorithm.

**Step 2.1**
Preprocessing each time series process with normalization method ($\frac{x - x_{\min}}{x_{\max} - x_{\min}}$).

**Step 2.2**
Stationary assumption should be studied for each time series process. If the process is not covariance stationary, the most suitable preprocessing method should be selected and applied to the model.

**Step 2.3**
Input variables for ANN model can be selected using Auto Correlation Function (ACF).

**Step 2.4**
Run and estimate ANN models and determination preferred ANN for each process.

**Step 2.5**
Forecast with selected ANN in Step 4.

**Step 3**
By considering data set as $S_\epsilon$ and applying reported algorithm\textsuperscript{14}, the best ANN structure (ANN*$) is identified. Run ANN$ for $S_\epsilon$.

**Step 4**
Previous steps are same as reported algorithm\textsuperscript{14}, but for continuing other steps, real value of output (input) for future period ($P_{real(n)}$/$C_{real(n)}$) is needed. In this study, the best efficiency with respect to n-1 for previous period are obtained for the future periods.

**Step 5**
Consider $E_i = P_{real(i)} - P_{ANN*(i)}$, $i=1,...,n-1$ for IO; and $E_i = C_{ANN*(i)} - C_{real(i)}$, $i=1,...,n-1$ for OO model.

**Step 6**
Define $x$ such that $x = \max\{E_i/P_{(ANN*)i}\}$, $i=1,...,n-1$ for IO model; and $x = \max\{E_i/C_{(ANN*)i}\}$, $i=1,...,n-1$ for OO model.

**Step 7**
Calculate margin energy (ME) as $ME = (1 - x)$ $C_{ANN*(n)}$. If value of $P_{real(n)}$ ($C_{real(n)}$) is set to ME, efficiency in the future period will be as good as the period with best efficiency in n-1 for previous periods. So, the more $P_{real(n)}$ production (the less $C_{real(n)}$ consumption) than ME in the future period will be planned, the more efficiency than n-1 for previous periods will be obtained.

**Step 8**
By applying remaining steps of ANN algorithm for complete dataset [after estimating $P_{real(n)}$ ($C_{real(n)}$)], efficiency scores of DMUs (n periods) in $S_\epsilon$ can be calculated.

**Results and Discussion**

**Case Study**
Proposed approach was applied to estimate energy consumption in Iranian railway Industry as follows:

**Step 1**
In present study, energy consumption (l) in each DMU is used as input variable, while TKM (t / km) and passenger per kilometer (PKM) are two outputs. Data are collected monthly for estimating efficient value of energy in future month and so, DMUs are the months.

**Step 2**
**Step 2.1**
Preprocessing each time series process with normalization method is done.
Step 2.2
There is no covariance stationary (Figs 1 & 2) but a more rigorous analysis is needed to verify this finding. Moreover, data is divided into two subsets and expected value (EV) and standard deviation (SD) of each subset are calculated as: subset 1, EV, 539153.5 & SD, 115591.6; and subset 2, EV, 786218.7 & SD, 144426.4. Thus, first difference method (\( y_t = x_t - x_{t-1} \)) is used to remove the trend from non-stationary processes.

Step 2.3
TKM (Fig. 3a), PKM (Fig. 3b) and energy (Fig. 3c) are the function of consumption in 1st and 12th lags.

Step 2.4
Mean absolute percentage error (MAPE) value for 20 ANN are calculated. It seems that 18th model (it has 18 neurons in a single hidden layer) has the lowest MAPE error and consequently is chosen as the preferred model for TKM process. Also, 5th model is selected as preferred model for PKM.

Fig. 1—Passenger per kilometer (PKM) data for passenger transport

Fig. 2—Tons per kilometer (TKM) data for freight transport

Fig. 3—Auto correlation function (ACF) chart for: a) TKM; b) PKM; and c) energy

Step 2.5
Values are forecasted with respect to selected ANN in Steps 2-4.

Steps 3 & 4
Consider energy and passenger/load as output and inputs of ANN respectively and run it for \( S_c \). Note that the value of energy for next month (\( C_{\text{real}(13)} \)) is not available, so before continuing the steps of ANN algorithm for evaluation, \( C_{\text{real}(13)} \) should be estimated.

Steps 5-7
\( C_{\text{real}(13)} \) is calculated such that the future month have the best energy efficiency with respect to 12 previous months of last year. So, \( E_i = C_{\text{ANN}^{13}(i)} - C_{\text{real}(i)}, i=1,\ldots,12; \)
\( x_i = \max\{ E_i/C_{\text{ANN}^{13}} \}, i=1,\ldots,12; \) and ME = \( 1-\max x_i \) \( C_{\text{ANN}^{13}} \). If value of \( C_{\text{real}(13)} \) is set to ME, energy efficiency in the future month will be as good as the best
in previous year. Therefore, if energy consumption is < ME in the next month is planned, then more energy efficiency than last year will be obtained. For this case, estimated ME (Table 1) is shown as ME = (1-0.0461) × 0.8776 = 0.8371. If improvement is 5%, than the best month in 12 previous months is considered. The best energy value for next month can be obtained as: 0.95 × 0.8371 = 0.7952. So the first row can be completed in the following manner: DMU, 1.85; predicted energy, 0.8776; real value, 0.7952; error (E_i), 0.0824; and $E_i/C_{(ANN^*) i}$, 0.0938.

**Step 8**

By applying ANN algorithm (OO model) for the complete dataset (after estimating $C_{real(13)}$), efficiency scores of all 12 months in last year and the first month in future year are obtained (Table 2). By estimated value for future energy consumption (2790541), energy efficiency for all months in previous year will be 100%.

**Examination of Algorithm in Noisy Situations**

One of the disadvantages of DEA is its lack of robustness due to existence of noise and complexity. However, due to intelligent, flexible and non-linear mechanism of ANN, noise and complexity could be noticeably decreased and hence robustness could be increased subsequently. An example is given to quantify and show the robustness of ANN versus DEA. Suppose that unreal outlier data is yielded from human error. Also, it is presumed that noisy or corrupted data is occurred in input variables. Suppose that energy consumption of Feb 2007 is changed from 24094249 to 34094249 (yielded from human error). MAPE is used to compare the results. MAPE value for corrupted DMU in proposed algorithm

<table>
<thead>
<tr>
<th>DMU</th>
<th>Predicted energy</th>
<th>Real</th>
<th>Error (E_i)</th>
<th>Shift</th>
<th>New shift</th>
<th>Efficiency</th>
</tr>
</thead>
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<tr>
<td>Jan 2007</td>
<td>0.8776</td>
<td>0.8371</td>
<td>0.0405</td>
<td>0.0405</td>
<td>0.8371</td>
<td>100.000</td>
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<tr>
<td>Dec 2007</td>
<td>0.8545</td>
<td>0.9076</td>
<td>-0.0531</td>
<td>0.0394</td>
<td>0.8150</td>
<td>89.801</td>
</tr>
<tr>
<td>Nov 2007</td>
<td>0.8567</td>
<td>0.9853</td>
<td>-0.1287</td>
<td>0.0395</td>
<td>0.8172</td>
<td>82.931</td>
</tr>
<tr>
<td>Oct 2007</td>
<td>0.8549</td>
<td>1.0000</td>
<td>-0.1451</td>
<td>0.0395</td>
<td>0.8154</td>
<td>81.544</td>
</tr>
<tr>
<td>Sep 2007</td>
<td>0.8582</td>
<td>0.9806</td>
<td>-0.1223</td>
<td>0.0396</td>
<td>0.8186</td>
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</tr>
<tr>
<td>Aug 2007</td>
<td>0.8299</td>
<td>0.8740</td>
<td>-0.0441</td>
<td>0.0383</td>
<td>0.7916</td>
<td>90.574</td>
</tr>
<tr>
<td>Jul 2007</td>
<td>0.8296</td>
<td>0.8274</td>
<td>0.0022</td>
<td>0.0383</td>
<td>0.7913</td>
<td>95.641</td>
</tr>
<tr>
<td>Jun 2007</td>
<td>0.9125</td>
<td>0.8704</td>
<td>0.0421</td>
<td>0.0421</td>
<td>0.8704</td>
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<tr>
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<td>0.8629</td>
<td>0.8827</td>
<td>-0.0198</td>
<td>0.0398</td>
<td>0.8231</td>
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<tr>
<td>Apr 2007</td>
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<td>0.0408</td>
<td>0.8438</td>
<td>95.331</td>
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<tr>
<td>Mar 2007</td>
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<td>-0.0110</td>
<td>0.0394</td>
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<tr>
<td>Feb 2007</td>
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</table>
versus DEA is as follows: DMU, Feb 2007; MAPE value of the proposed algorithm (A), 0.005; MAPE value of DEA (B), 0.44; and relative efficiency of algorithm over DEA (A/B), 88. From MAPE value for proposed algorithm, relatively small value of MAPE in the stated example (0.005) shows the capability of proposed algorithm in handling noisy and corrupted data. This example shows the superiority of proposed approach versus DEA with respect to noise and robustness.

**Precision of Proposed Algorithm**

Proposed algorithm is highly flexible because of non-linearity and universal approximations of neural networks. It is believed that ANN can be a potential alternative for measuring technical efficiency and can outperform other techniques. To investigate how precise current predictions are, the real data of future month (Jan 2008) was acquired from Iranian railway documentation for 2006 as 0.8562. As it can be seen, the real energy consumption (0.8562) has 2% error from predicted value (0.8776), which is quite acceptable. With the real data, true efficiency scores of the future month can be also calculated (Table 3), from which predicted efficiency scores and actual efficiency scores have no significant difference for future month.

**Conclusions**

This study proposed a highly unique flexible ANN algorithm to predict, estimate and evaluate DMUs performance without requiring any restrictive assumptions. Non-linearity of NNs in addition to its universal approximations of functions and its derivates makes the algorithm highly flexible. In this approach, value of a key controllable variable (s) (such as energy in the case study of railway) for next period was estimated so as the next period has highest efficiency with respect to the all previous periods in dataset. To show its applicability and superiority, it was applied to a case study, where energy efficiency of Iranian railway sector was determined using actual and projected data for months in 2004 and 2005. In this case, energy consumption (key variable) in future month was estimated in a way that the best efficiency score with respect to 12 last months would be obtained in that month. Therefore, proposed algorithm results and estimations not only are practicable for evaluation but also would be useful in future planning and would give more information to management about past, present and future. So this study can be a start point in optimization analysis by means of ANN. Although ANNs can be a potential alternative for measuring technical efficiency and can outperform other techniques when production process is unknown, there is still a lack of theoretical and empirical work in efficiency analysis.

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**References**


