Original Article

Predicting tanker freight rates using parsimonious variables and a hybrid artificial neural network with an adaptive genetic algorithm

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Abstract Short-term prediction of tanker freight rates (TFRs) is strategically important to stakeholders in the oil shipping industry. This study develops a hybrid TFR prediction model based on an artificial neural network (ANN) and an adaptive genetic algorithm (AGA). The AGA adaptively searches satisficing network parameters such as input delay size. The ANN iteratively optimizes a prediction network considering parsimonious variables and time-lag effects as predictors. Three parsimonious variables (crude oil price, fleet productivity and bunker price) are selected by a stepwise regression of TFR variables. The article compares the performance of its hybrid model with two traditional approaches (regression and moving average), as well as with the findings of existing ANN studies. The results of our model (root mean squared error (RMSE) = 11.2 WS) are not only significantly superior to the regression approach (RMSE = 21.6 WS) and the moving average approach (RMSE = 17.5 WS), but are even slightly superior to the results of existing ANN studies (RMSE = 14.6 WS–15.8 WS).

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Keywords: tanker freight rate; parsimonious variable; time-lag effect; artificial neural network; adaptive genetic algorithm; hybrid prediction model

Introduction

The prediction of tanker freight rates (TFRs) is essential for stakeholders in the oil shipping industry to make strategic business decisions such as freight rate pricing and hedging. TFR is a shipping price with a measurement unit of *world scale* (hereafter WS) for crude oil and oil products, which are delivered from one port to another (Zannetos, 1966). Both direct stakeholders (for example, tanker owners and shippers) and indirect stakeholders (for example, bankers, engineering companies and rating agencies) in the oil market are interested in the prediction of TFR (Celik *et al*, 2009). However, an accurate prediction of TFR is difficult because of its complexity and mutability (Lyridis *et al*, 2004; Randers and Goluke, 2007; United Nations, 2010; Xu *et al*, 2011).

TFR is characterized by the complex interactions between supply and demand in the oil shipping industry. Tanker demand is affected by many oil-related variables such as international oil trade, crude oil price and oil consumption (Koopmans, 1939; Zannetos, 1966; Stopford, 2009). Tanker demand is fairly inelastic against TFR because transportation costs have a negligible effect on oil demand (Glen and Martin, 2005). Tanker supply is influenced by many tanker-related variables such as tanker fleet size, available tonnage, new building activity and bunker price (Koopmans, 1939; Zannetos, 1966; Beenstock and Vergottis, 1989; Lyridis *et al*, 2004). Contrary to tanker demand, tanker supply is relatively elastic against TFR. For example, a high TFR promotes the ordering of new tankers, which increases tanker supply. The effects of tanker supply, however, are reflected in the tanker market with a time delay because of the impact of manufacturing lead time.

To capture the dynamics and fluctuations of TFR in a prediction model, three different approaches have been applied in existing studies. The statistical approach develops a statistical equation of TFR with tanker demand variables (for example, transport demand) and supply variables (for example, total tanker tonnage) as predictors (Randers and Goluke, 2007). The time series approach formulates an autoregressive function of TFR with time-lagged TFR as a predictor (Veenstra and Franses, 1997; Kavussanos and Alizadeh, 2002; Kavussanos, 2003; Adland and Cullinane, 2005; Batchelor *et al*, 2007; Duru, 2010; Chen *et al*, 2012). Lastly, the artificial neural network (ANN) approach builds a prediction model by utilizing historical relationships of TFR with tanker market variables and time-lagged TFR (Li and Parsons, 1997; Lyridis *et al*, 2004; Santos *et al*, 2013).

The ANN approach has been widely advocated as a reliable alternative to the statistical and time series approaches. The time series approach provides a better short-term forecast than the statistical approach, whereas the statistical approach is a better long-term predictor than the time series approach. The prediction performance of these two traditional approaches of TFR, however, is debatable

(Alizadeh and Talley, 2011). In contrast, the ANN approach is able to accurately model seasonality, trends and cyclical movements of a response (Gorr, 1994). In addition, the ANN approach can estimate the non-linear nature of a response by universal approximate functions (Zhang *et al*, 1998; Khashei and Bijari, 2010). These features contribute to an improved forecasting performance of the ANN approach relative to the two traditional approaches (Franses, 1991; Foster *et al*, 1992).

A study by Li and Parsons (1997) is the first to have attempted to apply ANN in TFR forecasting. The authors developed two ANN models with three predictors: (i) time-lagged TFR, (ii) Drewry tanker demand index and (iii) total capacity of active tankers. The first model (known as a univariate model) uses only the time-lagged TFR, whereas the second model (known as a multivariate model) employs the above three variables. The performances of the univariate model (root mean squared error (RMSE) = 73 WS) and multivariate model (RMSE = 64 WS) are not promising. A later study by Lyridis *et al* (2004) applies ANN in predicting TFR for very large crude carriers (VLCCs). The performance (RMSE = 14.6 WS) of the ANN model in that study is excellent. The prediction method, however, requires many input variables ($n = 13$) as predictors, which are difficult to obtain and which might cause problems of multicollinearity.

To improve prediction accuracy, many attempts to combine ANN and genetic algorithm (GA) have been made in other prediction domains. Hybrid models are becoming a common practice in the interest of enhancing prediction performance relative to individual models (Atighehchian and Sepehri, 2013). ANN has pre-eminent learning ability, but its performance relies on its network parameters (for example, neuron number), for which no acceptable rules exist in terms of predetermining them (Acharya *et al*, 2003). To overcome this limitation, GA is employed in the determination of near-optimal combinations of network parameters. Many existing studies have proposed and investigated hybrid prediction models involving ANN and GA (Koehn, 1994; Kamp and Savenije, 2006; Kim, 2006; Dhanwani and Wadhe, 2013; Pallavi and Vaithiyanathan, 2013; Reshamwala *et al*, 2014; Majidnezhad, 2015). So far, however, a hybrid prediction model has not been applied to the prediction of TFR.

This study develops a hybrid TFR prediction model based on ANN and an adaptive genetic algorithm (AGA), which considers parsimonious variables and time-lag effects. The AGA adaptively determines a satisficing combination of network parameters, while ANN builds a TFR model capable of reliable short-term prediction. In addition, parsimonious variables and time-lag effects were employed in the prediction model. Our study evaluates the performance of the hybrid prediction model and compares its performance with the two traditional approaches to prediction (regression and moving average approaches), as well as with the findings of existing ANN studies.

Analysis of the Characteristics of the Tanker Market

A dependency structure (Figure 1) of tanker market variables with TFR was identified via comprehensive review of the relevant literature (Koopmans, 1939; Zannetos, 1966; Stopford, 2009; Wijnolst and Wergeland, 2009). Tanker demand is affected by oil trade volume, crude oil prices and average haul. For example, oil trade volume links positively to tanker demand. Tanker supply is influenced by active fleet, fleet productivity, bunker prices and time-lagged TFR (feedback). For example, active fleet associates directly with tanker supply. Finally, time charter rates, which refer to a long-term (for example, 1 year) charter price, are closely related to TFR, which is a spot price.

The time-lag effects of the aforementioned seven variables on TFR were analysed by correlation analysis. Correlation coefficients (r) of each variable with TFR were calculated for various time lags (Month 1–Month 10), as shown in Figure 2. For example, the correlation coefficient of bunker price increased gradually until time-lag 7, and then started to decrease. An increasing trend in correlation coefficients over time implies the existence of a more significant time-lag effect. Two variables (crude oil price and bunker price) showed trends of increasing correlation coefficients.

The autocorrelation coefficients of TFR itself were analysed for various time lags (Month 1–Month 10), as shown in Figure 3. The autocorrelation coefficient value peaked at time-lag 1 (0.88) and, from there, decreased gradually as the time lag increased. The autocorrelation coefficients were significantly different from 0 until time-lag 7 ($t=2.31$, $P=0.01$). This implies that time-lag effects of TFR do exist, and they thus need to be considered in the development of a prediction model.

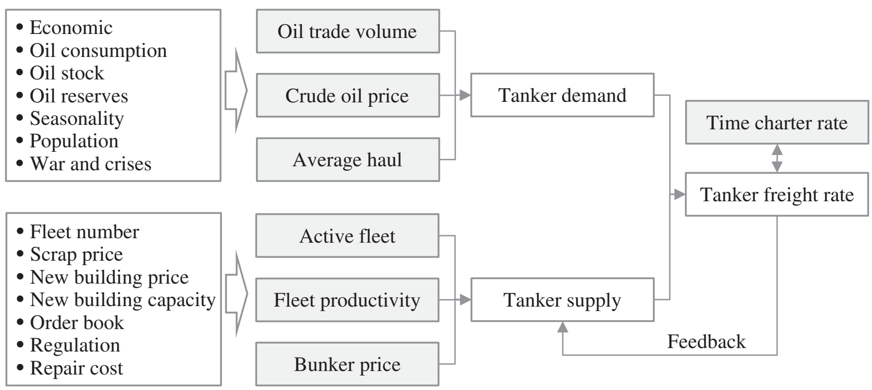

Figure 1: Dependency structure of tanker market variables with TFRs.
NB: The variables of interest are shaded.

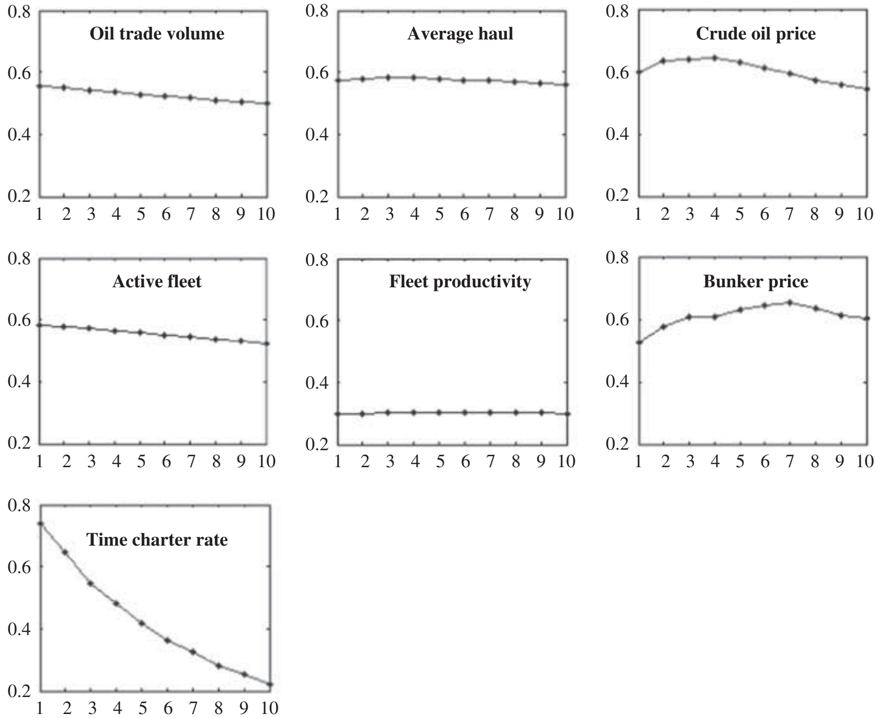

Figure 2: Correlation coefficients (y-axis) of time-lagged variables (x-axis; unit: month) with TFRs.

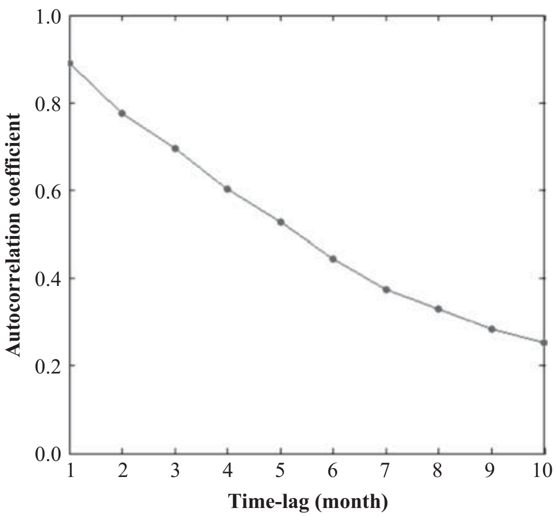

Figure 3: Autocorrelation coefficients of TFRs.

Finally, three parsimonious variables were selected by stepwise regression ($\alpha_{in} = 0.05$ and $\alpha_{out} = 0.1$), using the seven variables of TFR. According to the results of the stepwise regression, the variables of *fleet productivity* ($P = 0.019$), *crude oil price* ($P = 0.001$) and *bunker price* ($P = 0.002$) were significant. This suggests that a prediction model using these three parsimonious variables as predictors is statistically adequate. The adjusted R^2 and RMSE values of the stepwise regression model were 46.9 per cent and 4.6 WS, respectively. The variance inflation factor (VIF) values of fleet productivity, crude oil price and bunker price were 1.1, 3.1 and 3.3, respectively, which are less than the value of a decision criterion (VIF = 5) to determine multicollinearity (O'Brien, 2007).

Proposed Hybrid Prediction Model

The hybrid prediction model proposed in this article combines ANN and AGA, as shown in Figure 4. ANN constructs a neural network for the prediction of TFR by training with given network parameters such as the size of input delay. The AGA searches a near-optimal combination of network parameters, which improves the accuracy of ANN.

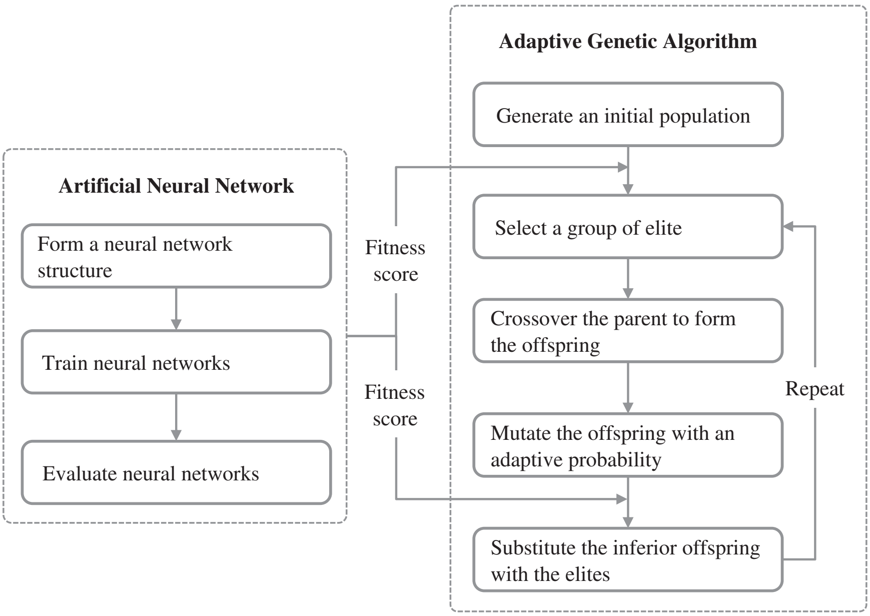

Figure 4: Process of the proposed hybrid prediction model.

Artificial neural network

On the basis of the characteristics of the tanker market, the network structure of ANN is determined. ANN can be classified into static and dynamic categories. The static, or feed-forward network, is a network that does not involve either feedback elements or time delay. The output is computed from the inputs through feed-forward connections (Svozil *et al*, 1997; Zhang *et al*, 1998; Beale *et al*, 2014). On the other hand, a dynamic network is a network in which output depends on network inputs, as well as on previous inputs and outputs (Beale *et al*, 2014). To capture the characteristics of the tanker market in a prediction model, this article employs a dynamic network (known as the NARX network), consisting of a feed-forward network with tapped delay lines at the hidden layer from inputs and outputs, as shown in Figure 5.

From the training data of inputs p and targets t, the weights and biases are iteratively adjusted to minimize the performance measure. The most well-known performance measure for numeric output is the mean squared error (MSE). MSE is the average squared error between the outputs a and the true targets t, as given by:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{1}$$

where N is the number of training data.

The neural network training algorithm uses gradient information to determine how to adjust weights and biases so as to minimize the performance measure of MSE. The gradient is calculated by using a backpropagation (Abbasi *et al*, 2008; Raza and Liyanage, 2010), which performs numerical computations backward through the network. The Levenberg–Marquardt algorithm updates

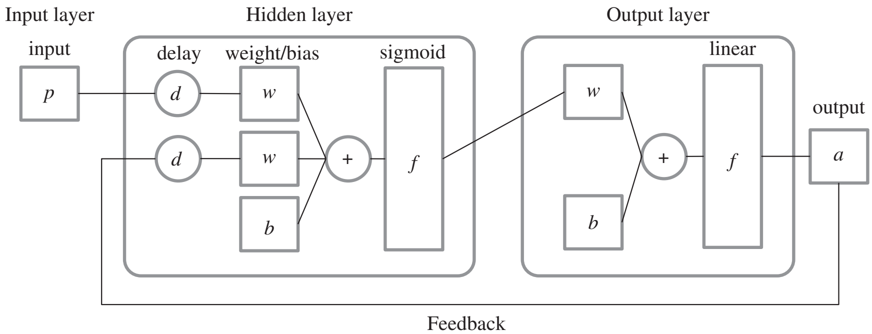

Figure 5: NARX network for the prediction of TFRs.
NB: p = input, d = delay, w = weight, b = bias, f = function, a = output.

the weights and biases by iteratively computing the update rule, as follows:

$$w_{k+1} = w_k - (H + \mu_k diag[H])^{-1} J_k^T e_k \quad (2)$$

where w_k is a vector of weights and biases, k is an iteration number, H (signifying the Hessian matrix) is the second derivative of the performance measure, J (signifying the Jacobian matrix) is the first derivative of the performance measure, μ is a step size and e is a vector of errors.

Adaptive genetic algorithm

The specific AGA here determines iteratively a near-optimal combination of four network parameters, including (i) input delay size, (ii) output delay size, (iii) training data proportion and (iv) neuron number. The chromosome for each of the four network parameters is coded with four two-digit numbers, for a total of eight digits, as follows. A two-digit number for input delay size (Range: 1–12), a two-digit number for output delay size (Range: 1–12), a two-digit number for training data proportion (Range: 50–70) and a two-digit number for the neuron number (Range: 1–30). Thus, an initial population group (Size: 50) is randomly generated.

A small group of elite members in the population (top 10 per cent) is reserved to pass on good chromosomes, to be inherited by the next generation (the offspring). A unique characteristic of biological evolution is the process of natural selection (Summanwar *et al*, 2002; Kellegoz *et al*, 2010; Datta *et al*, 2011). The strong members in a population survive, thereby ensuring that the chromosomes best fitting a species to its environment are inherited by the offspring (that is, survival of the fittest). Adopting this concept, this study's AGA selects 10 per cent of the elite population to preserve characteristics to be inherited by the next generation.

A single-point crossover with roulette-wheel selection is applied to the population to establish the offspring. The roulette-wheel selection chooses members from the population based on their fitness score (Rardin, 1998). Therefore, members with higher fitness scores (1/MSE) have a greater chance of being selected. The single-point crossover passes on the chromosomes of the selected members (the parent) to the offspring generation to inherit. The single-point crossover in this study exchanges the chromosomes of two parents at a random position to generate two offspring members.

Mutations in the chromosomes of the offspring are triggered with an adaptable mutation probability represented by P_m. Diversity in the offspring is very important for successful evolution (Yun, 2006), as it expands a search space. Hence, the AGA in this study adaptively adjusts the mutation probability based on the homogeneity of the offspring (Bekiroglu *et al*, 2009; Lee *et al*, 2011).

A mutation probability is determined by $P_m = 1/\mathrm{SD}$, where SD is the standard deviation of the chromosomes in the offspring. If the SD of the offspring is small (because of high homogeneity in the offspring), then a high mutation probability is applied to diversify the members of the offspring (Jung, 2012).

Finally, the inferior members of the offspring generation are replaced by the reserved elite members of the original population. The entire AGA process is repeated until an incumbent solution seems unchanged during a certain number of generations (for example, 500).

Performance Evaluation

Data for the three parsimonious variables and TFR was collected for the period 1983–2003 (21 years). The three parsimonious variables selected by stepwise regression include (i) fleet productivity (Unit: ton-miles per annum), (ii) crude oil price (Unit: $ per barrel) and (iii) bunker price (Unit: $ per tonne). The TFR data (Unit: WS) for VLCCs on the Ras Tanura–Rotterdam route was used to compare the performance of the hybrid prediction model with the findings of existing ANN studies (Lyridis *et al*, 2004; Mehrara *et al*, 2010).

The prediction results of the hybrid model for the near-term (1 month) future showed satisfactory accuracy, as shown in Figure 6. The RMSE and mean absolute error values of the hybrid model were 11.2 and 9.0 WS for the testing data.

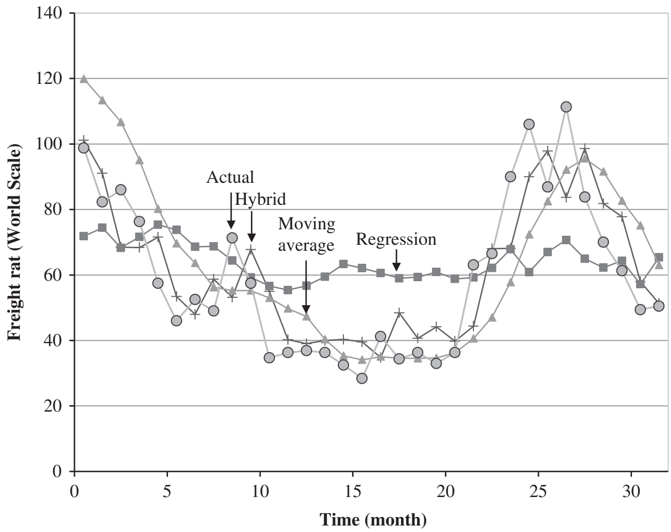

Figure 6: Prediction results for the hybrid model and traditional approaches.

The near-optimal network parameters selected by AGA were 77 per cent for the learning data proportion (11.5 per cent for validation data and 11.5 per cent for testing data), 4 for the input delay size, 6 for the output delay size and 8 for the neuron number.

The prediction accuracy of the hybrid model was superior to the prediction accuracy of the moving average model and the regression model. The moving average model with length 5 was developed as:

$$a_{i+1} = \frac{\sum_{j=i-4}^{i} t_j}{5} \tag{3}$$

The regression model (adjusted $R^2 = 0.50$) was built using the three parsimonious variables as:

$$a_{i+1} = -59.6 + 0.003x_{1i} + 3.08x_{2i} - 0.405x_{3i} \tag{4}$$

where x_1 is fleet productivity, x_2 is crude oil price and x_3 is bunker price. The RMSE of the hybrid model (11.2 WS) was 40 and 73 per cent smaller than the RMSE values of the moving average model (16.6 WS) and the regression model (22.4 WS). In addition, the coefficient of determination between the actual targets and the outputs predicted by the hybrid model ($R^2 = 0.72$) was 1.4 and 2.3 times larger than the coefficient of determination between the actual targets and the outputs of the moving average model ($R^2 = 0.57$) and the regression model ($R^2 = 0.26$).

The forecasting accuracy of the hybrid model was slightly better than the findings reported in studies by Lyridis *et al* (2004) and Mehrara *et al* (2010). The RMSE of the hybrid model (11.2 WS) was 17 per cent smaller than the RMSE of the model of Lyridis *et al* (14.6 WS), which uses similar data in terms of tanker type, period and route. In addition, the RMSE of the hybrid model was 27 per cent lower than the model of Mehrara *et al* (15.8 WS), which considers the same type of tankers (VLCC) as here.

An AGA can effectively improve the prediction performance of ANN, as demonstrated in Figure 7. The prediction performance (14.5 WS) of an initial network parameter was similar to the performance results (14.6 WS) of Lyridis *et al* (2004). However, the prediction accuracy improved as the generations of AGA increased. The RMSE at generation 1000 was 11.2 WS, showing an approximate improvement of 29 per cent over the initial performance. Therefore, it can be concluded that the AGA used in this study is successfully able to search a satisficing combination of network parameters.

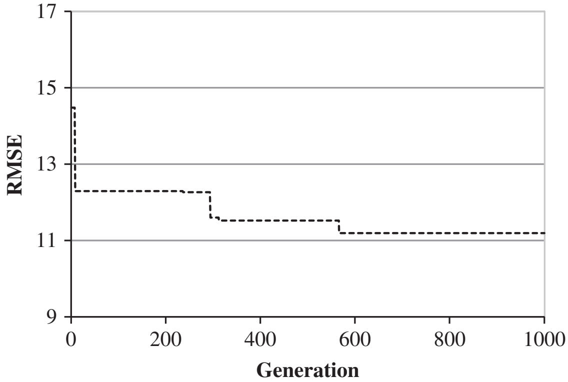

Figure 7: RMSE of the hybrid prediction model at each generation of the AGA.

Conclusions

This study developed a simple and accurate hybrid model of ANN and AGA, employing three parsimonious variables (fleet productivity, crude oil price and bunker price) and time-lag effects for the short-term prediction of TFR. Use of the parsimonious variables in the prediction model improved its practical applicability and minimized problems of multicollinearity. The hybrid prediction model successfully overcome the limitations of ANN with the use of the AGA, resulting in more accurate prediction results than the results of traditional approaches and existing studies. The hybrid prediction model proposed in this study can be utilized in short-term (1 month) prediction of TFR.

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