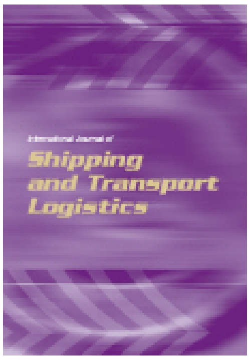

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Logistics performance index estimating with artificial intelligence

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Abstract: The World Bank has presented the logistics performance index (LPI) to measure and rank countries' international logistics performance. Based on six different components, the impact of each LPI component should be further investigated. In this paper, performance criteria are ranked using MGGP. This ranking approach is the first kind of study that enables countries to prioritise and adjust measures to evaluate their logistics performance better. MGGP is a recent promising approach among machine learning techniques, and it is capable of creating linear or nonlinear prediction models. LPI datasets consisting of 790 records collected between 2010–2018 are used to train and test the proposed MGGP approach. MGGP help address the logistics performance based on the relative importance of factors. The simulation results show the superiority of the MGGP approach predicting the LPI score. The prediction equation generated by MGGP can be helpful, for policymakers and researchers in logistics, in establishing logistics plans.

Keywords: logistics; logistics performance index; LPI; multi-gene genetic programming; MGGP; artificial intelligence.

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1 Introduction

Logistics has an essential role in today's global trade (Wong and Tang, 2018; Denizhan and Konuk, 2013; Gürbüz et al., 2019). Due to the emerging importance of global business, the success of evaluating and measuring countries' logistics performance is of significant concern. Different scales such as trade flow, productivity, customer satisfaction, etc., are proposed to determine the competitiveness of the countries and essential for international logistics providers, developing and improving the national logistics performance (Martí et al., 2017). The most used and traceable logistics performance index is the world-bank index.

World Bank researchers created the logistics performance index (LPI) in 2007. Several updated versions of LPI have been published respectively in 2010, 2012, 2014, 2016 and 2018 (Arvis et al., 2018). Today, the LPI plays a vital role in international trade in many countries (Martí et al., 2017), and LPI provides challenges and opportunities. Also, LPI helps to assess and enhance the performance of logistics of 160 countries. In LPI, countries are ranked on six components:

1 customs
2 infrastructure
3 ease of arranging shipments
4 quality of logistics services
5 tracking and tracing
6 timeliness.

Each country has an LPI score, and top-scored countries remain relatively unchanged, generally high-income European countries. However, for most other countries, it is demonstrated that the proposed LPI scores identify consequential awareness on logistics performance in trade logistics.

There are several studies in the literature on logistics performance evaluation of country-based using the LPI index. These studies are mainly focused on the effects of the LPI index on global competition and international trade. Stanley et al. (1998) surveyed logistic performance measurements, where logistic performance is the factor in the success of any organisation. Asset management, cost, and customer service are evaluated for efficiency and quality. Martí et al. (2014) investigated the effect of LPI index parameters on the commercial achievements of developing countries such as Africa, South America, Far and the Middle East, and Eastern Europe. They use the data from 2007 to 2012 and show that the LPI index has an essential role in developing international trade in these countries. Martí et al. (2014) developed an approach based on a data envelopment analysis (DEA) to forecast a synthetic index of logistics performance (DEALPI) for multiple criteria decision making and test the logistics performance of the countries with LPI. Roy et al. (2018) presented a two-stage methodological framework. First, the LPI dataset is clustered, and then the multivariate adaptive regression spline technique is linked with the clustered LPI dataset to extract meaningful insights on logistics performance. The mapping among LPI dimensions and per capita GDP is modelled using the countries' economic vitality levels and logistics performance (Roy et al., 2018). In another study, the success of logistics and marketing activities of 153 German and Turk companies is examined using the LPI index (Akdoğan and Durak, 2016). The results revealed are similar to those in the LPI report. The national rankings are obtained by SOLP (sustainable operational logistics performance) using LPI (Rashidi and Cullinane, 2019). Jhawar et al. (2014) assessed the logistic performance of India based on LPI, while Faria et al. (2015) used LPI to analyse the logistics performance of Brazil. Rezaei et al. (2018) proposed a weighted LPI where the best-worst method (BWM) is used to determine the weights for the components of the proposed LPI. A questionnaire set answered by 107 experts is used for multi-criteria decision analysis, and the optimal weights are determined by BWM, finding the values by minimising the maximum absolute differences fr the set are minimised. Kunadhamraks and Hanaoka (2008) proposed a method based on fuzzy set theory and examined the logistics performance of the intermodal freight transportation of Thailand.

The main concern about the underlying nature of the LPI studies mentioned above is that the LPI score of each country is calculated using a weighted normalised average with equal weights. We strongly believe it is necessary to examine which component of the LPI is more critical for the logistics performance of each country. So, the motivation of this study is to determine the relationships of the parameters within the LPI score. This study is the first literature to make an accurate forecast by decisive weighted criteria with multi-gene genetic programming (MGGP). Again, for the first time in the literature, the prediction of the LPI index guide countries to determine their local priorities. The method presented in this study aims to guide countries to increase their performance in the LPI data from year to year. Prediction of the LPI is in the literature does not exist; however, it is accepted as one of the best parameter prediction and analysis methods within the scope of computational intelligence.

Computational intelligence (CI) methods provide robust models and perform several tasks, including optimisation, prediction, and classification. These models must be carefully designed to obtain accurate predictions. To deal with an accurate prediction equation, a systematic methodology is required. That is, obtaining and selecting the most appropriate equation for a given problem is most challenging. Genetic programming (GP) is a CI method to achieve compact models for system behaviour by automatically generating and designing computer programs represented by tree structures (Koza, 1992). GP is a powerful approach to achieving a simplified prediction equation without assuming a prior form of the existing relationships. Multi-gene genetic programming (MGGP) is a recent variant of GP and proposed by Searson et al. (2010). MGGP formulates the nonlinear behaviours by using the model framework election capability of the classical GP and parameter estimation power of traditional regression. In MGGP, a generalised prediction model is constructed using multiple genes and approximates the coefficients of these multiple genes. Because of its prediction capabilities, MGGP has been applied to several problems (Searson et al., 2010; Bayazidi et al., 2014; Gandomi and Alavi, 2012a, 2012b; Gandomi et al., 2016; Garg et al., 2014a, 2014b; Garg and Lam, 2015). Also, the recent work from Pedrino et al. (2019) investigated an MGGP approach for detecting the landing of distributed generation (DG). Using specific scenarios, Tzu et al. (2019) evolved an MGGP to deal with the flat typically ventilated roof's heat acquisition per square metre. Hadi and Tombul (2018) used the wavelet coherence transformation (WCT) to focus on evolving the critical variables and their scales to predict the monthly downstream flow. They developed an MGGP-ANN model that only selects the scales produced by continuous wavelet transformation (CWT). Hoang et al. (2017) established a machine learning model based on MGGP and multivariate adaptive regression splines (MARS) to deal with chloride diffusion prediction. Pires et al. (2010) developed an MGGP approach to estimate the daily average of PM10 concentrations on the following day. Garg et al. (2014a) presented a framework via SRM-MGGP to determine the mathematical relationship among the factor of safety (FOS) and the six input variables of cohesion, nail inclination angle, frictional angle, nail length, the slope angle of 3D nailed slope and slope height. Pandey et al. (2015) modelled gas yield production using MGGP. Garg et al. (2014b) investigated the performance of three artificial intelligence (AI) techniques, namely, MGGP, artificial neural network, and support vector regression. Garg and Lam (2015) proposed an ensemble-based MGGP technique to evolve a model to estimate the power consumption.

Although these successful MGGP applications exist in other fields, commonly for prediction, modelling, and formulation, none is found on the application of MGGP to logistics problems. It is the first study that presents MGGP for logistics performance prediction modelling to the best of our knowledge. In this paper, the MGGP model is first developed, and then the performance of the developed model is distinguished considering different control parameters. In performance comparison, World Bank datasets with 790 records collected between 2010–2018 are used. It is important to emphasise that this study was not conducted to test the effectiveness of the MGGP method. Its purpose is to show the predictability of the LPI data using CI-based methods.

The remainder of the paper is organised as follows: Section 2 briefly explains the LPI index. The proposed MGGP methodology used for estimation purposes is given in Section 3. Section 4 gives the experimental train and test results of MGGP. Finally, the discussion and conclusion are given in Section 5 and Section 6.

2 Logistics performance index

Efficient transport and logistics activities strengthen not only the foreign economy but also the domestic economy. As logistics connects the domestic economy to the international economy, robust logistics and operational processes can facilitate international trade (Azmat, 2017). Assessing the trade facilitation and the logistics of the countries is critical, especially for the business competitiveness of the emerging countries. For this reason, the World Bank first published LPI in 2007, but since 2010 LPI has been published every two years by ranking 160 countries. LPI analyses the critical differences among countries and supplies an overview of countries' customs procedures, logistics costs, land and sea transport infrastructure, etc. Also, countries specify their strategic development plans and targets on their LPI score. Besides, the companies identify the issues on the receiving country's logistics competence, the availability of efficient supply chains, and transport infrastructure by the LPI score (Arvis et al., 2018; Faria et al., 2015).

LPI is composed of several vital components. These LPI components are illustrated in Figure 1 and briefly defined as below (Arvis et al., 2018; Faria et al., 2015):

- Customs: The efficiency of customs and border management clearance.
- Infrastructure: It is crucial to facilitate customs clearance to maintain quality products and move the goods.
- International shipments: Simplicity of arranging competitively priced shipments.
- Logistics service quality: The logistics services and customer requirements should be fulfilled by logistics service providers.
- Tracking and tracing: To manage the logistics flow from source to destination to shorten the transit time and adopt the shipments changes.
- Timeliness: An essential measurable component is that shipments reach the destination within the scheduled or expected delivery time.

Figure 1 Six key components of LPI (see online version for colours)

In the current LPI, the importance (weights) of each component of LPI shown in Figure 1 is regarded as equal. However, the impact of LPI components should be analysed. Thus, a model is created using MGGP to discover the relationships between LPI components in this paper.

The LPI calculation is done by the World Bank as follows: response from a country with randomly selected but not uniform probability – weights selected to improve sampling towards uniform probability. Mainly, country i is selected with probability (N – ni)/2N; ni is the sample size of country i to date, and N is the total sample size. The International LPI is a summary indicator that combines data on six criteria into one aggregate measure. LPI was created from these six signals using principal component analysis (PCA), a standard statistical technique used to decrease the dimensionality of a dataset. The scores are normalised by subtracting the sample mean and dividing by the standard deviation before PCA is performed. The output from the PCA is a single indicator – LPI, which is the weighted average of these scores. Component loads represent the weight given to each original indicator when forming the international ROI. The international LPI is approximately a simple average of indicators because it is similar for all six loads in Table 1. Even though the PCA is rerun for each version of the LPI, the weights endure very stably annually (LPI Methodology, https://wb-lpi-media.s3.amazonaws.com/LPI%20Methodology.pdf). For this reason, it is argued that there is a harmony between wide varieties of LPI. On the other hand, different methods such as MGGP will help countries set targets for the next year by calculating the weights consistent with the results. Also, the LPI report says that the LPI has two critical restrictions. The first is the experience of international shipping companies. This situation may not reflect the broad logistics environment in lower-income countries that often rely on traditional operators. International and traditional operators may also differ in their interactions with government agencies and their service levels. Second, for landlocked countries and small island states, the LPI may reflect access issues outside the country, difficult to pass (LPI Methodology, https://wb-lpi-media.s3.amazonaws.com/LPI%20Methodology.pdf). In our opinion, this paper also helps to eliminate these limitations with MGGP methods. The data and country analysis added every year would be estimated with the MGGP, and the differences can be reflected.

Table 1 Component loadings for the international LPI

Component	*Weight*
Customs	0.40
Infrastructure	0.42
International shipments	0.40
Logistics service quality	0.42
Tracking and tracing	0.41
Timeliness	0.40

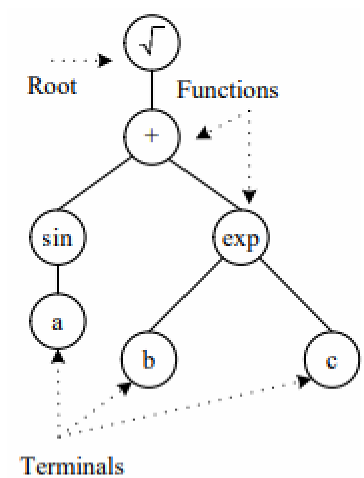
3 Multi-gene genetic programming

The GP is an evolutionary machine learning algorithm proposed by Koza (1992). GP evaluates predictive models for challenging computational problems. Unlike linear regression, GP does not require a prior defined model and any assumptions to develop models. GP mimics the biological evolution operations, which include reproduction, crossover, and mutation in nature. GP naturally progresses computer programs for answering a specific task through these operations and finally generates a model represented by a tree structure.

First, GP randomly generates individual programs. Then, using genetic operators (crossover and mutation), individuals are selected based on their fitness values, producing new individuals for the next generations. The crossover generates new individuals by swapping the subtrees. The mutation operator generates new mapping relations by changing the mapping number of random mapping the tree structures. The generated programs are expanded and enhanced until better fitness values are acquired. At the end of the MGGP iteration, the optimal solution to the given problem is the best individual.

GP model formed by a set of functional or terminal set of elements such as arithmetic operators (+, ×, /, or –), mathematical functions (sin, cos, tan, log, etc.), Boolean operators (AND, OR, NOT, etc.), or logical definitions (IF or THEN). A terminal set can be variables (a, b, c, etc.) and constant values. The model has a tree architecture, a hierarchically structured GP model consisting of functions and terminals illustrated in Figure 2.

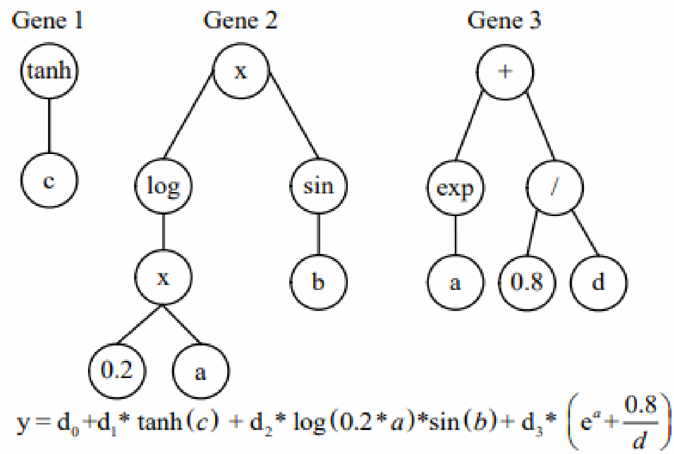
Figure 2 A hierarchically structure GP model



Multi-gene genetic programming (MGGP) refers to evolutionary algorithms and a robust variant of GP (Searson et al., 2010; Cobaner et al., 2016a, 2016b). MGGP designs a practical model with its adaptability and versatility. Note that MGGP integrates the model structure selection operations in GP with the least square technique. MGGP can produce a mathematical formula using a linear mix of low-order nonlinear transformations of the input-output variables.

Although classical GP utilises a single tree structure, MGGP represents the model by a few genes (each gene is a tree structure) with a weighted linear combination of each gene (d1, d2, d3, …) plus a bias term (0 d) to forecast an output y. A model tree structure with four inputs (a, b, c, d) and one output (y) in MGGP is depicted in Figure 3.

Figure 3 A model tree structure diagram in MGGP



Two critical control parameters of MGGP are the maximal number of genes and the maximal tree depth. These two parameters are selected based on the previous users' experience or trial-and-error because these two parameters impact the complexity of the model. More expressions on MGGP parameters can be seen in Searson et al. (2010) and Gandomi and Alavi (2012a).

4 Experimental results

Numerical experiments are carried out on a personal computer with an Intel Core i5-3470 M CPU at 3.20 GHz and 8 GB of RAM under Windows 10 64-Bit. To evaluate the performance of MGGP generating an equation for LPI prediction, the World Bank dataset with 790 records collected between 2010 – 2018 data is employed. The World Bank dataset was divided into 80% for train and 20% for test in the simulations. The inputs of MGGP are customs score, infrastructure score, international shipments score, logistics service quality score, tracking and tracing score, timeliness score; the output of MGGP is the LPI score. The parameter settings of the MGGP used in the simulations are shown in Table 2. The parameters given in Table 2 are chosen according to the suggested values in the literature.

Table 2 The parameter settings of MGGP

Parameters	*Values*
Function set	{'times', 'plus', 'mult3'}
Initialisation	Ramped half-and-half
Tournament size	10
Elitism	0.04%
Crossover probability rate	0.85
Reproduction probability rate	0.10
Mutation probability rate	0.05

Simulations are conducted to examine the performance of the MGGP method for different numbers of population (Pop), the number of maximum generations (Ng), the maximum number of genes (Mg), and the maximum depth of the tree (Md) for comparison. The simulation results are given in Table 3.

Table 3 The experimental results

Pop	*Ng*	*Mg*	*Md*	$RMSE_{train}$	*MAE*	*MARE*	R^2_{train}	$RMSE_{test}$	*MAE*	*MARE*	R^2_{test}
150	200	2	3	0.0253000	0.019	0.713	0.99805	0.0253691	0.019	0.714	0.99812
100	200	2	3	0.0046896	0.004	0.135	0.99993	0.0044753	0.004	0.130	0.99994
50	200	2	3	0.0046896	0.004	0.135	0.99993	0.0044753	0.004	0.130	0.99994
50	100	2	3	0.0327859	0.025	0.935	0.99675	0.0317907	0.025	0.927	0.99699
50	100	4	3	0.0327859	0.025	0.935	0.99675	0.0317907	0.025	0.927	0.99699
50	100	4	2	0.0042906	0.003	0.126	0.99994	0.0040681	0.003	0.119	0.99995
50	100	5	2	0.0042906	0.003	0.126	0.99994	0.0040681	0.003	0.119	0.99995
50	*100*	*5*	*3*	*0.0039844*	*0.003*	*0.117*	*0.99995*	*0.0038698*	*0.003*	*0.113*	*0.99996*

Also, the performance of MGGP is evaluated using mean square error (MSE), mean absolute error (MAE), mean absolute relative error (MARE), and the determination coefficient (R^2) values. Parameters values are function set {'times', 'plus', 'mult3'}; initialisation – ramped half-and-half; tournament size – 10; elitism – 0.04%; crossover probability rate – 0.85; reproduction probability rate – 0.10; mutation probability rate – 0.05 in training and testing phases, and these values are listed in Table 3. The MSE, MAE, and MARE are calculated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[(Overall\ LPI)_{i_{actual}} - (Overall\ LPI)_{i_{predicted}}\right]^2 \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(Overall\ LPI)_{i_{actual}} - (Overall\ LPI)_{i_{predicted}}\right| \tag{2}$$

$$MARE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(Overall\ LPI)_{i_{actual}} - (Overall\ LPI)_{i_{predicted}}}{(Overall\ LPI)_{i_{actual}}}\right| * 100 \tag{3}$$

It can be observed from Table 3 that a more considerable value of Mg and Md result in better modelling performance. The best-obtained values are given in italic, shown in Table 3. The best model equation obtained using MGGP is as follows:

$$\begin{aligned} Overall\_LPI_{score} &= 0.166 * custom_{score} + 0.145 * infrastructure_{score} + 0.194 * shipments_{score} \\ &+ 0.166 * logistics\ service\ quality_{score} + 0.16 * tracking\ tracing_{score} \\ &+ 0.17 * timeliness_{score} \end{aligned} \tag{4}$$

From Table 3, when the train performance of the model in equation (4) is evaluated in terms of R^2, RMSE, MAE and MARE; R^2 value is close to 1, and RMSE, MAE, and MARE values are considerably low. Even for the test data, similar results (as in the training phase) are obtained. These better test results reveal the generalisation capability of the MGGP model. Also, from the results and the obtained equation, if a country wants to keep the total LPI score high, that country should focus primarily on shipments activities with the highest impact value, followed by timeliness, custom, quality, and the latest infrastructure. At the same time, scoring has turned into an easily measurable structure with the MGGP equation.

5 Discussion

It should be emphasised that the simulation results contribute a guiding evaluation for all countries in the LPI index. Besides, the previous data of the countries are weighted by MGGP. According to the results obtained, international shipments are the first significant factor that affects all countries' scores, thus directly increasing their logistic performance. The logistics quality and timeliness are the second significant factors that are equal. Generally, customs are considered the priority for many countries; however, it is the third significant factor from the model obtained by MGGP. The fourth significant factor is tracking and tracing, and finally, the last factor is the infrastructure. This importance can help the companies and countries reduce their logistics costs and improve logistics performance and legislator rules. When this index is used as feedback, it can contribute to all non-developed or developing countries.

6 Conclusions

Enhancing logistics performance is essential for the trade growth of countries, and LPI is a unique, efficient tool to evaluate the logistics performance of the countries worldwide. For this reason, in this paper, an accurate and compact prediction model is obtained and proposed by MGGP, a new machine learning approach using the relationships among six components for the LPI score. None of the previous studies have examined the relative importance of the factors of LPI for logistics performance. Although in LPI, all components are studied to be equally important, the equation presented in this paper reveals the relative importance of each component on the LPI score for the logistics industry.

This study has social and scientific indications. The proposed equation can improve the logistics performance measurements and guidance to underdeveloped or developing countries' insight into where to target and how to improve their policies for growth and integration. As for future work, the modelling results of the equation obtained by MGGP can be compared to other recent machine learning methods.

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References

Akdoğan, M.Ş. and Durak, A. (2016) 'Logistic and marketing performances of logistics companies: a comparison between Germany and Turkey', *Procedia – Social and Behavioral Sciences*, Vol. 235, pp.576–586 [online] https://doi.org/10.1016/j.sbspro.2016.11.084.

Arvis, J.F., Ojala, L., Wiederer, C., Shepherd, B., Raj, A., Dairabayeva, K. and Kiiski, T. (2018) *Connecting to Compete 2018: Trade Logistics in the Global Economy*, World Bank Washington, DC, License: CC BY 3.0 IGO [online] https://openknowledge.worldbank.org/handle/10986/29971; http://documents.worldbank.org/curated/en/576061531492034646/pdf/128355-WP-P164390-PUBLIC-LPIfullreportwithcover.pdf (accessed 20 July 2019).

Azmat, G. (2017) 'The logistics performance effect in international trade', *The Asian Journal of Shipping and Logistics*, Vol. 33, No. 4, pp.4279–4288.

Bayazidi, A.M., Wang, G.G., Bolandi, H., Alavi, A.H. and Gandomi, A.H. (2014) 'Multi-gene genetic programming for estimation of elastic modulus of concrete', *Mathematical Problems in Engineering*, Vol. 2014, 10pp, Article ID: 474289.

Cobaner, M., Babayigit, B. and Dogan, A. (2016b) 'Estimation of groundwater levels with surface observations via genetic programming', *J. Am. Water Works Assoc.*, Vol. 108, pp.E335–E348 [online] https://doi.org/10.5942/jawwa.2016.108.0078.

Cobaner, M., Babayigit, E. and Babayigit, B. (2016a) 'Estimation of groundwater level with genetic programming using meteorological data', *Nigde University J. Eng. Sci.*, Vol. 5, No. 2, pp.177–187.

Denizhan, B. and Konuk, K.A. (2013) *Quality Management in Reverse Logistics, Cases of Damage in Third-Party Logistics Businesses*, Springer, DOI: 10.1007/978-1-4471-4537-0_8.

Faria, R., Nunes, D.S.C., Souza, D. and Vieira, J.G.V. (2015) *Evaluation of Logistics Performance Indexes of Brazil in the International Trade* [online] http://dx.doi.org/10.1590/1678-69712015/administracao.v16n1p213-235.

Gandomi, A.H. and Alavi, AH. (2012a) 'A new multi-gene genetic programming approach to nonlinear system modeling, Part I: materials and structural engineering problems', *Neural Comput. Appl.*, Vol. 21, No. 1, p.171.

Gandomi, A.H. and Alavi, A.H. (2012b) 'A new multi-gene genetic programming approach to nonlinear system modeling, Part II: geotechnical and earthquake engineering problems', *Neural Comput. Appl.*, Vol. 21, No. 1, p.189.

Gandomi, A.H., Sajedi, S., Kiani, B. and Huang, Q. (2016) 'Genetic programming for experimental big data mining: a case study on concrete creep formulation', *Automation in Construction*, Vol. 70, pp.89–97.

Garg, A. and Lam, J.S.L. (2015) 'Improving environmental sustainability by formulation of generalized power consumption models using an ensemble based multi-gene genetic programming approach', *Journal of Cleaner Production*, Vol. 102, pp.246–263 [online] https://doi.org/10.1016/j.jclepro.2015.04.068.

Garg, A., Garg, A., Tai, K. and Sreedeep, S. (2014a) 'An integrated SRM-multi-gene genetic programming approach for prediction of factor of safety of 3-D soil nailed slopes', *Engineering Applications of Artificial Intelligence*, Vol. 30, pp.30–40 [online] https://doi.org/10.1016/j.engappai.2013.12.011.

Garg, A., Vijayaraghavan, V., Mahapatra, S.S., Tai, K. and Wong, CH. (2014b) 'Performance evaluation of microbial fuel cell by artificial intelligence methods', *Expert Systems with Applications*, Vol. 41, pp.1389–1399, DOI: 10.1016/j.eswa.2013.08.038.

Gürbüz, F., Eski, İ. and Denizhan, B. (2019) 'Prediction of damage parameters of a 3PL company via data mining and neural networks', *J. Intell. Manuf.*, Vol. 30, pp.1437–1449, DOI: 10.1007/s10845-017-1337-z.

Hadi, S.J. and Tombul, M. (2018) 'Monthly streamflow forecasting using continuous wavelet and multi-gene genetic programming combination', *Journal of Hydrology*, Vol. 561, pp.674–687 [online] https://doi.org/10.1016/j.jhydrol.2018.04.036.

Hoang, N.D., Chen, C.T. and Liao, K.W. (2017) 'Prediction of chloride diffusion in cement mortar using multi-gene genetic programming and multivariate adaptive regression splines', *Measurement*, Vol. 112, pp.141–149 [online] https://doi.org/10.1016/j.measurement.2017.08.031.

Jhawar, A., Garg, S.K. and Khera, S.N. (2014) 'Analysis of the skilled workforce effect on the logistics performance index – case study from India', *Logistics Res.*, Vol. 7, p.117, DOI: 10.1007/s12159-014-0117-9.

Koza, J.R. (1992) *Genetic Programming: On the Programming of Computers by Means of Natural Selection*, MIT Press, Cambridge, Mass.

Kunadhamraks, P. and Hanaoka, S. (2008) 'Evaluating the logistics performance of intermodal transportation in Thailand', *Asia Pacific Journal of Marketing and Logistics*, Vol. 20, No. 3, pp.323–342 [online] https://doi.org/10.1108/13555850810890084.

LPI Methodology [online] https://wb-lpi-media.s3.amazonaws.com/LPI%20Methodology.pdf (accessed 20 July 2019).

Martí, L., Martín, J.C. and Puertas, R. (2017) 'A DEA-logistics performance index', *Journal of Applied Economics*, Vol. 20, No. 1, pp.169–192 [online] https://doi.org/10.1016/S1514-0326(17)30008-9.

Martí, L., Puertas, R. and García, L. (2014) 'The importance of the logistics performance index in international trade', *Applied Economics*, Vol. 46, No. 24, pp.2982–2992 [online] https://doi.org/10.1080/00036846.2014.916394.

Pandey, D.Y., Pan, I., Das, S., Leahy, J.J. and Kwapinski, W. (2015) 'Multi-gene genetic programming based predictive models for municipal solid waste gasification in a fluidized bed gasifier', *Bioresource Technology*, Vol. 179, pp.524–533 [online] https://doi.org/10.1016/j.biortech.2014.12.048.

Pedrino, E.C., Yamada, T., Lunardi, T.R. and Vieira Jr., C.S.M. (2019) 'Islanding detection of distributed generation by using multi-gene genetic programming-based classifier', *Applied Soft Computing Journal*, Vol. 74, pp.206–215 [online] https://doi.org/10.1016/j.asoc.2018.10.016.

Pires, J.C.M., Alvim-Ferraz, M.C.M., Pereira, M.C. and Martins, F.G. (2010) 'Prediction of PM10 concentrations through multi-gene genetic programming', *Atmospheric Pollution Research*, Vol. 1, pp.305–310 [online] https://doi.org/10.5094/APR.2010.038.

Rashidi, K. and Cullinane, K. (2019) 'Evaluating the sustainability of national logistics performance using data envelopment analysis', *Transport Policy*, Vol. 74, pp.35–46 [online] https://doi.org/10.1016/j.tranpol.2018.11.014.

Rezaei, J., Roekel, W.S. and Tavasszy, L. (2018) 'Measuring the relative importance of the logistics performance index indicators using best-worst method', *Transport Policy*, Vol. 68, pp.158–169 [online] https://doi.org/10.1016/j.tranpol.2018.05.007.

Roy, V., Mitra, S.K., Chattopadhyay, M. and Sahay, B.S. (2018) 'Facilitating the extraction of extended insights on logistics performance from the logistics performance index dataset: a two-stage methodological framework and its application', *Research in Transportation Business & Management*, Vol. 28, pp.23–32 [online] http://dx.doi.org/10.1016/j.rtbm.2017.10.001.

Searson, D.P., Leahy, D.E. and Willis, M.J. (2010) 'GPTIPS: an open-source genetic programming toolbox for multi-gene symbolic regression', *Proceedings of the International MultiConference of Engineers and Computer Sci.*, IMECS, Hong Kong, Vol. 1, p.17.

Stanley, E., Fawcett, M. and Cooper, B. (1998) 'Logistics performance measurement and customer success', *Industrial Marketing Management*, Vol. 27, pp.341–357 [online] https://doi.org/10.1016/S0019-8501(97)00078-3.

Tzuc, O.M., Hernández-Pérez, I., Macias-Melo, E.V., Bassam, A., Xamán, J. and Cruz, B. (2019) 'Multi-gene genetic programming for predicting the heat gain of flat naturally ventilated roof using data from outdoor environmental monitoring', *Measurement*, Vol. 138, pp.106–117 [online] https://doi.org/10.1016/j.measurement.2019.02.032.

Wong, W.P. and Tang, C.F. (2018) 'The major determinants of logistic performance in a global perspective: evidence from panel data analysis', *International Journal of Logistics Research and Applications*, Vol. 21, No. 4, pp.431–443 [online] https://doi.org/10.1080/13675567.2018.1438377.