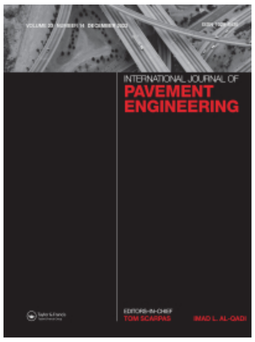

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A hybrid approach based on regression analysis and ANN for non-destructive asphalt road density measurement

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ABSTRACT
The performance characteristics of asphalt pavement, including durability and resistance to deformation, are linked to its density. Accurate measurement of density is, therefore, critical for the evaluation of asphalt pavement performance, which is commonly performed with the coring method (CM) and the Pavement Quality Indicator (PQI). The former provides high accuracy, but it is destructive, inefficient and requires additional repairs to the pavement after the cores are taken. In contrast, the PQI-based method is non-destructive and efficient, but its accuracy is comparatively lower. The accuracy of the PQI-based method can be improved by applying data processing analysis techniques such as regression analysis and artificial neural network (ANN). This paper proposes a hybrid approach that combines both regression models and ANN models. The density and temperature measured with a PQI are input into the regression models for optimisation. In addition, the optimised regression-model-predicted density is then used to train ANN models. The effectiveness of the proposed approach is validated by the results of the field study.

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Asphalt road density; artificial neural network; regression analysis; non-destructive method; optimisation

1. Introduction

The asphalt pavement is typically laid in layers, with each layer being compacted using a heavy roller. Once a layer is compacted, its performance characteristics can be determined by its density. A higher density results in better resistance to deformation and cracking, as well as improved durability (Leng *et al.* 2011).

The coring method (CM) is straightforward and accurate for measuring the density of asphalt pavement (Ameri *et al.* 2014). It involves dividing the pavement into different lots and sub-lots and extracting a single core sample from each sub-lot for laboratory analysis (NZS 2008, 2014). The density measured by CM is called core density. One significant drawback of this method is that the extraction of core samples results in the creation of numerous holes in the asphalt pavement. Thus, it is a so-called destructive method. Additionally, the process of taking and measuring core samples is very time-consuming.

To mitigate the drawbacks of the coring method, non-destructive methods for measuring the density of asphalt pavement have been proposed (Ziari 2010). These methods rely on measurement devices that don't cause any damage during the measurement process. One of the commonly used devices is the nuclear density gauge (NDG), which utilises a radiation source to activate gamma photons, which are received by a set of detectors after being scattered from the collision with the pavement. The number of photons received by the detectors is correlated with the density of the asphalt pavement (Malpass and Khosla 2002, IAEA 2005). Though it can achieve good measurement accuracy, its application is greatly limited by the potential hazards associated with nuclear radiation exposure.

An alternative non-destructive method without nuclear radiation hazards is based on the Pavement Quality Indicator (PQI). PQI is an electromagnetic-based density gauge whose electrical sensing field is sensitive to the pavement density of the region (*active region*) it covers (KTC 2003, Ziari 2010). Any change in pavement density will cause a corresponding change in the sensing field, which is processed by a built-in algorithm for density (called PQI density) estimation (Ziari 2010). However, the accuracy of PQI measurements is affected by various factors other than density, such as pavement composition, moisture, and temperature.

It is thus necessary to develop an approach to improve the density measurement accuracy of the PQI-based method, considering many benefits it can offer. Considering a PQI as a sensor, conventional data processing and analysis techniques used for general sensors can be applied (Negnevitsky 2011). One of the popular techniques is regression analysis, which can be used to infer the relationship between a dependent variable (core density) and multiple independent variables (e.g. temperature and PQI density) (KTC 2003, NCDOT 2005). By developing and optimising regression models using data samples, the measurement accuracy of the PQI device can be improved (Fitzgerald 2002, Al-Qadi 2010, Ziari 2010).

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Alternatively, other data-driven approaches, such as the artificial neuron network (ANN), can be applied to improve the PQI's measurement accuracy. ANN has been proven to be a viable technique for processing data when conventional methods such as regression analysis are insufficient for establishing the relationships among data (Tian and Shang 2006, Bashiri and Geranmayeh 2011, Puigarnavat 2015, Khadse *et al.* 2017). An ANN is comprised of artificial neurons arranged in multiple layers (Negnevitsky 2011). The neurons in different layers are linked with weights, producing the output in the output layers. The performance of an ANN model is determined by the weights that are assigned in the so-called training process to minimise the error between the predicted and the target density. Once the ANN model has been trained, it can be applied to real-time data to generate optimised outputs. It has been applied to monitor the quality of the asphalt pavement construction with good performances (Commuri and Zaman 2008, Commuri *et al.* 2011, Rajiah *et al.* 2021).

Though regression analysis or ANN has been applied to improve the measurement accuracy of the PQI method, there is still room for improvement to make it closer to that of the CM. Motivated by the potential of combining the strengths and advantages of both methods, this paper proposes a novel hybrid approach utilising regression analysis and ANN to enhance the accuracy of the PQI device to measure asphalt road density. It includes an optimised regression model to predict the density, which is then used as the input of an ANN model. In order to optimise the regression model and train the ANN models, data samples consisting of the core density, PQI density, and PQI-measured temperature of the asphalt pavement from various projects are utilised. The performance of the proposed hybrid model is then compared with that of the regression and ANN models, respectively, to show its effectiveness.

The remaining parts of the paper are organised as follows. Asphalt payment density measurement methods are described in Section 2. The regression, ANN, and hybrid models are presented in Section 3. Data collection is discussed in Section 4. The structure of the regression model is optimised in Section 5. The performances of the regression model, ANN, and hybrid model are respectively described in Sections 6 and 7. The conclusion is given in Section 8.

2. Asphalt pavement density measurement methods

2.1. Coring method (CM)

CM is a common destructive method involving core sample extraction and laboratory tests. Typically, at least one core sample is extracted from every 300 m^2 area of asphalt pavement, with the location chosen randomly within the designated area (NZS 2008). The core sample is then sent to a laboratory where its density is determined in a process involving the following steps: weighing the mass of the dry sample, coating it with a thin wax layer, weighing the mass of the sample with the wax layer, and weighing the sample in water with a specialised balance (NZS 2014). The precise core density can then be computed using the following equation:

$$\rho_{core} = \frac{m_1 \rho_w \rho_{wax}}{\rho_{wax}(m_2 - m_3) - \rho_w(m_2 - m_1)} \tag{1}$$

where ρ_{core} is the core density of sample (kg/m^3), ρ_{wax} is the density of the paraffin wax (kg/m^3), ρ_w is the density of water (kg/m^3), m_1 is the mass of the dry sample (kg), m_2 is the mass of the sample with the wax layer(kg), m_3 is the mass of the sample in water(kg).

CM is regarded as the most reliable technique for determining the density of asphalt pavement (Ameri *et al.* 2014). However, it is inefficient due to the core sample extraction and subsequent laboratory testing phases and is costly for additional costs and workload for the recovery of the pavement with holes which significantly compromise the overall quality of the pavement (Ziari 2010).

2.2. Pavement quality indicator (PQI)

PQI is a non-destructive device applied to measuring the density of asphalt pavement by utilising electromagnetic induction (TranstechSystems 2019). As shown in Figure 1, a ground region, an isolation ring, and an active region are used for measuring the complex permittivity by the PQI (TranstechSystems 2020). By adding an electric field to a pure substance, the complex permittivity can be derived through Debye's equation.

In contrast to pure materials, asphalt is a composite material composed of aggregate, asphalt binder, and a small amount of air. Due to the lower relative permittivity of air, the air void has a significant impact on the pavement's complex permittivity (Porubiaková and Komačka 2015). A predetermined algorithm in the PQI converts the measured complex permittivity into the air void percentage and, subsequently, to the density. However, the presence of water within the air void influences the PQI's density measurement since the permittivity of water varies with temperature (Leng 2012). Hence, PQI also measures temperature as a factor affecting the accuracy of density measurement. To improve the PQI's accuracy in density measurement, an optimised model can be developed that accurately incorporates the temperature-density relationship. One way to achieve this objective is to apply data processing techniques such as artificial neural networks (ANN) and regression analysis.

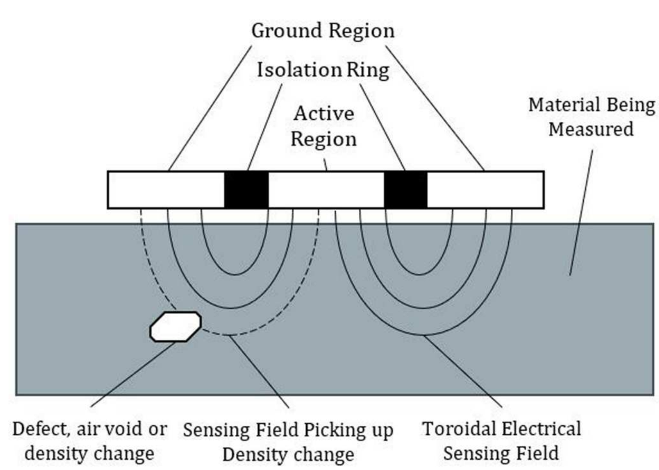

Figure 1. The operational theories of a PQI.

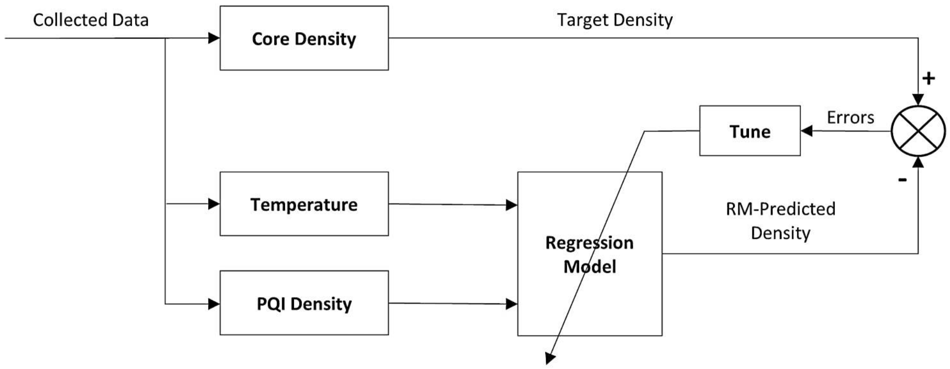

Figure 2. The schematic of the approach based on the regression models.

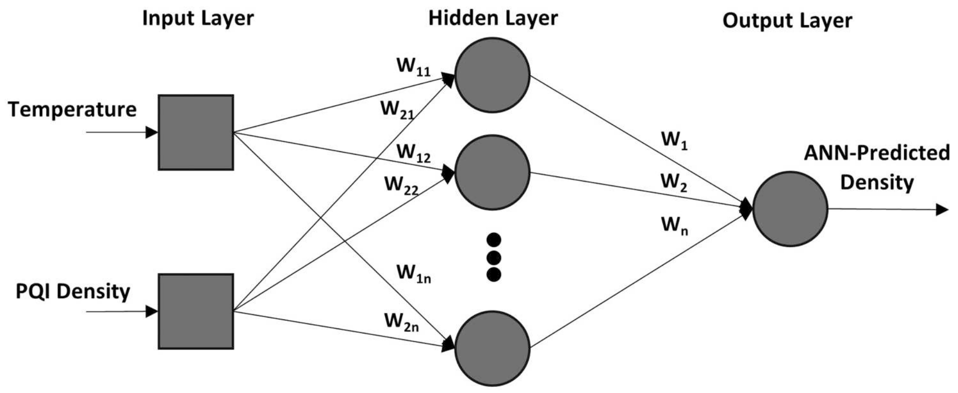

Figure 3. The architecture of the ANN model applied in this approach.

3. Regression, ANN and hybrid models

Three kinds of models are applied in this research, including linear/non-linear regression models, an ANN model, and a hybrid model combining the regression models and the ANN model.

3.1. Linear and nonlinear regression models

In this part, the relationship between PQI density, temperature, and core density is established in regression analysis. The following linear and nonlinear regression models are used:

$$\rho_{core} = a + b*\rho_{pqi} + c*T \tag{2}$$

$$\rho_{core} = a + b*\rho^{c}_{pqi} + d*T^{e} \tag{3}$$

where ρ_{core} and ρ_{pqi} are the core and PQI density, respectively, T is the surface temperature and a, b, c, d, e are the coefficients to be found through minimisation the error between the output of the regression model (regression-model-predicted density) and the actual measurement value (core density). The nonlinear model (Equation (3)) is a simple model and is regarded as nonlinear model 1. A more complex nonlinear model will be established after the coefficients c and e of nonlinear model 1 are identified.

The Curve Fitting Tool in MATLAB, a software package for the optimal design of regression models, is used to determine the coefficients. As shown in Figure 2, pairs of PQI density and temperature are input into a model for which the initial values of the coefficients are set first. The predicted density is computed and compared with the corresponding core density. The error between them is then calculated and used to adjust the coefficients through the optimal design approaches like least squares. The above process is repeated until the error is minimised to the desired level. The optimised models are then used for calculating the final predicted density.

3.2. An ANN model

As a powerful computation model, an ANN consists of artificial neurons, which are organised into various layers. As shown in Figure 3, the ANN used in this study consists of 3 layers. The neuron in the input layer transfers the input density and temperature to the neurons in the hidden layer. The

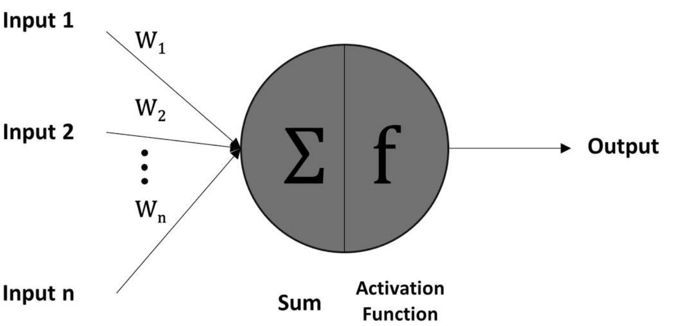

Figure 4. An artificial neuron in an ANN model.

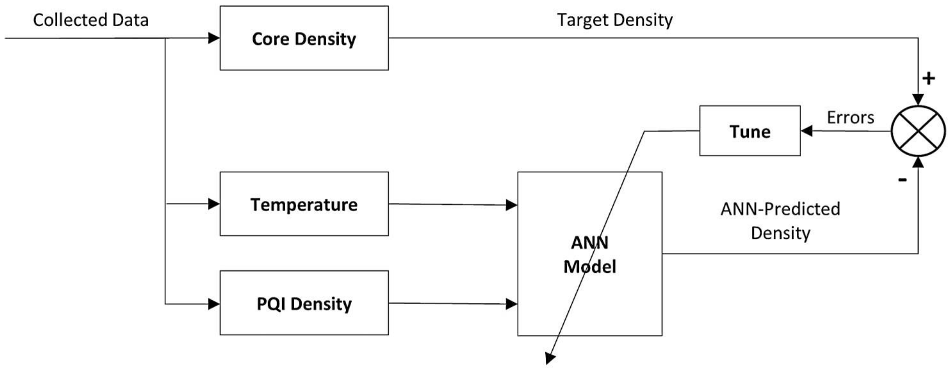

Figure 5. The schematic of the approach based on the ANN model.

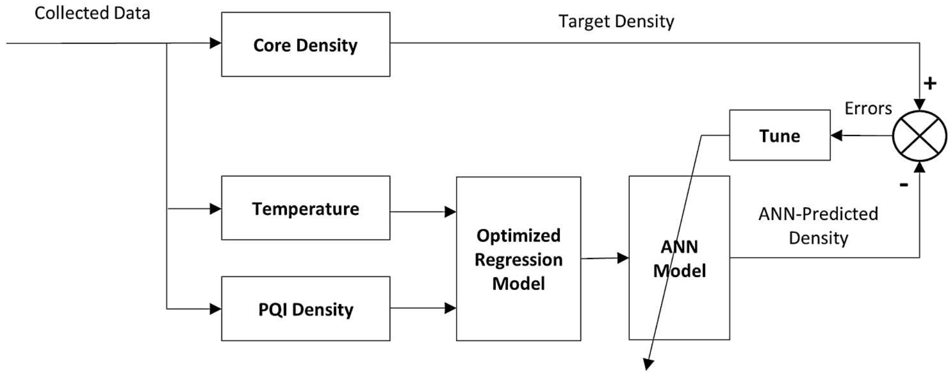

Figure 6. The schematic of the proposed hybrid approach.

latter neuron, shown in Figure 4, computes the weighted sum of the inputs, which is used to determine the output of the neuron via an activation function. The output is then regarded as the input of the neuron in the output layer. The neuron conducts the same computation process and outputs the ANN-predicted density.

As shown in Figure 5, pairs of PQI density and temperature are input to train the ANN models. The ANN training process is conducted via the ANN Toolbox in MATLAB software. The initial weights are preset automatically. The ANN-predicted density is the output of the ANN model and is then compared with the core density. The error between them is computed for adjusting the weights. After the training process, an ANN model with optimised weights and minimised errors is named a trained ANN. It is applied to calculate the final predicted density.

3.3. Hybrid approach based on the regression and ANN models

The ANN model itself sometimes may not perform well. A preprocessed approach, like regression analysis, can be used to further improve the performance of the ANN model. Thus, a hybrid approach is proposed and it consists of two parts. In the first part, the linear and nonlinear regression models are established and optimised. It is the same process that is mentioned in Section 3.1. In the second part, an ANN model is established and trained. It is similar to the process mentioned in Section 3.2. The only difference is that the

Figure 7. A PQI device measuring the density at the marked spot.

input data for training the ANN model is the density predicted by the optimised regression model. It is so-called a hybrid approach. The schematic of it is shown in Figure 6.

4. Data collection

Totally 240 data samples are collected, including PQI density, core density, and temperature. The first 75 samples are

Table 1. The coefficients of the regression models.

	a	*b*	*c*	*d*	*e*
Linear model	1533.00	0.23	8.15	–	–
Nonlinear model 1	1928.00	$3.26*10^{-8}$	2.97	0.08	2.01

Table 2. The coefficients of the optimised regression regression model.

	a	*b*	*c*	*d*	*e*	*f*	*g*
Nonlinear model 2	$-1.55*10^4$	$2.42*10^{-6}$	−0.03	−0.01	1.46	27.39	−8.13

Table 3. The performance of the regression models.

	R^2	RMSE (kg/m^3)
Original	0.68	67.98
Linear model	0.77	31.69
Nonlinear model 1	0.60	41.81
Nonlinear model 2	0.81	28.87

Table 4. The performance of the ANN model.

	R^2	RMSE (kg/m^3)
Training group	0.85	25.38
Validation group	0.87	22.67
Test group	0.81	29.66
Overall	0.85	25.79

collected in the *Northern Corridor Improvement* project with the support of Fulton Hogan Company, New Zealand. The main objective of the project is to build a new connection linking two motorways, SH18 and SH1, in Auckland, New Zealand. The connection is the place where the samples are collected. The theoretical maximum density is 2350 kg/m^3. The data collection process contains four parts. Firstly, after the asphalt pavement compaction, the spots for later measurement are marked. Secondly, a PQI-380 device, as shown in Figure 7, is employed to measure the density and the surface temperature of the pavement. Thirdly, an asphalt core is extracted at each spot. Finally, all the cores extracted are transferred to the Fulton Hogan Lab Centre for density measurement.

The remaining 165 samples are collected in the New Asphalt Mix Trial project initiated by Fulton Hogan. In this project, a new kind of asphalt mix specific for the thin layer is developed and tested on the internal pavement of the Fulton Hogan Silverdale branch in Auckland, New Zealand. The paving area is divided into three sections, and 58, 56, and 51 samples are collected in each section, respectively. The theoretical density is around 2300 kg/m^3. The data collection process is similar to the project mentioned above, and the same PQI device is employed.

5. Optimization of the regression models

The regression analysis is conducted first by employing the linear and nonlinear regression models. The coefficients of the models derived from the regression analysis are shown in Table 1.

According to the results, the coefficients *c* and *e* of the nonlinear model 1 are both between 2 and 3. It indicates that a more complex model with cubic and quadratic terms may better fit the input and target data. A new model (nonlinear model 2) is established as follows:

$$\rho_{core1} = a + b*\rho_{pqi}^3 + c*T^3 + d*\rho_{pqi}^2 + e*T^2 \quad (4)$$

$$\rho_{core2} = f*\rho_{pqi} + g*T \quad (5)$$

$$\rho_{core} = \rho_{core1} + \rho_{core2} \quad (6)$$

The coefficients of the nonlinear model 2 are shown in Table 2. *b*, *d*, and *f* are the coefficients of the cubic, quadratic, and linear terms of the PQI density, respectively. The absolute value of *f* is much larger than that of *b* or *d* (27.39 compared with $2.42*10^{-6}$ or −0.01). Hence, the linear term of the PQI density plays the most important role. By comparing the terms of temperature, the absolute value of *e* or *g* is larger than 1, while that of *c* is smaller than 1 (1.46 or −8.13 compared with −0.03). Thus, both the linear and quadratic terms of temperature significantly contribute to improving the PQI density, but the contribution of the cubic term is minor. Overall, based on the coefficients of the nonlinear model 2, the linear term of the PQI density and the linear and quadratic terms of the temperature affect the accuracy of the model significantly.

6. Performance of the regression models

The performance of the three models is then evaluated. The measurement accuracy of each model is evaluated by computing the root mean squared error (RMSE) through the following equation:

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n}(X_i - Y_i)^2}{n}} \quad (7)$$

where *X* and *Y* are the core density and the model-predicted density, respectively. *n* is the total number of densities.

The performance of each model can also be measured by using the coefficient of determination (R^2), which reflects the overall closeness of the predicted densities to the core densities and is calculated by the following equation:

$$R^2 = \frac{(\Sigma_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y}))^2}{\Sigma_{i=1}^{n}(X_i - \bar{X})^2\Sigma_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (8)$$

where X_i and Y_i are the core density and model-predicted density, respectively. $\bar{X}$ and $\bar{Y}$ are the average values of X_i and Y_i, respectively. *n* is the total number of densities.

The performance of the optimised regression models is shown in Table 3. The row starting with 'Original' shows the original performance of PQI without the assistance of any regression model, resulting in a lower correlation. In contrast, the linear model exhibits an improved accuracy, reducing the RMSE from 67.98 to 31.69 kg/m^3. It also performs better by increasing the R^2 value from 0.68 to 0.77. In terms of nonlinear model 1, it shows a very different performance. Compared with the original performance, its RMSE is reduced while its R^2 value is also reduced. It is not an optimised model. However, its contribution is that its coefficients can be used to optimise the order numbers of terms mentioned in Section 5. The nonlinear model 2 performs its excellent accuracy. Its RMSE is only 28.87 kg/m^3, which is the smallest RMSE among all the regression models and less than half of the original RMSE

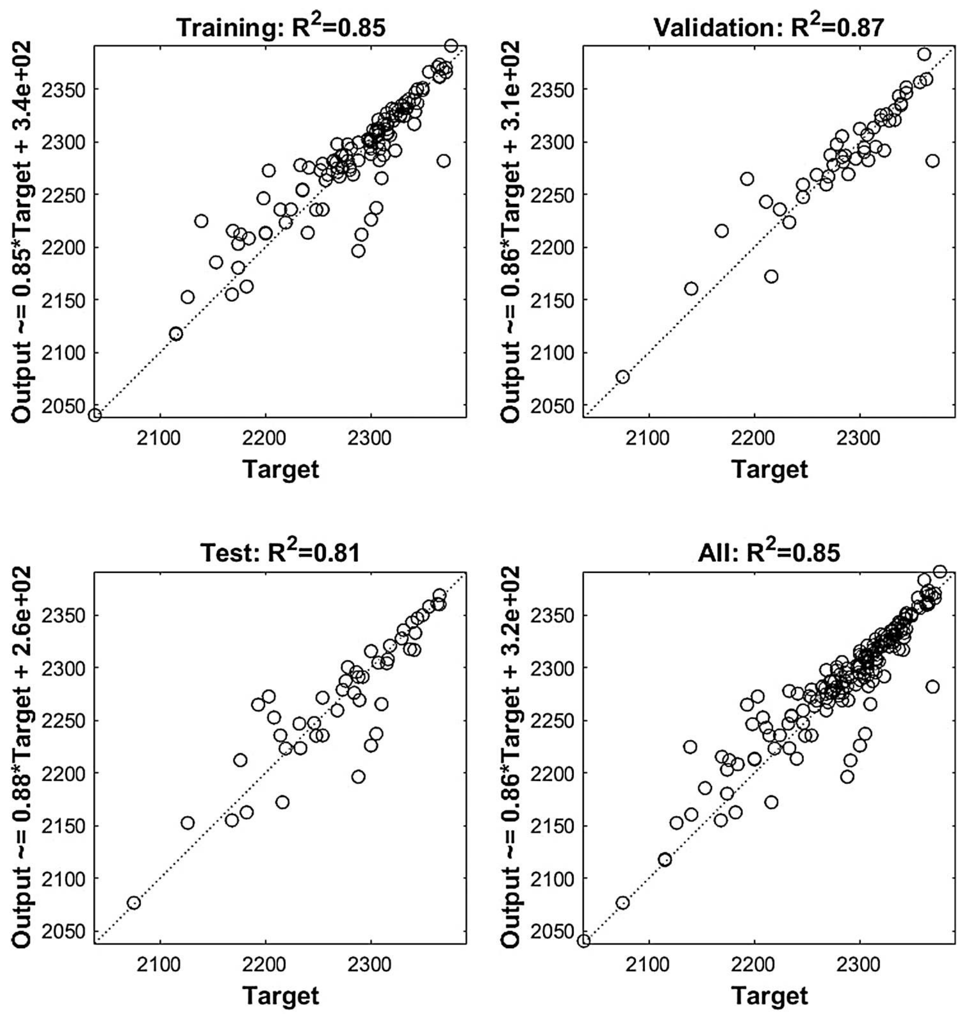

Figure 8. The performance of the ANN model.

(67.98 kg/m^3). The regression performance of the nonlinear model 2 is also the best. Its R^2 value is 0.81, which is the highest among all other R^2 values. This R^2 value is increased a lot in comparison with the original one (0.68). Thus, nonlinear model 2 is the optimised regression model.

7. Performance of the ANN and the hybrid model

Before the ANN training process, the input and target data are split into training (60%), validation (20%), and test (20%) groups. The training group data is used to train the ANN model directly. The validation group data is used to test the ANN model during training and stop training when it is overfitted. The test group data is used to test the model after training.

The performance of the ANN model is evaluated and presented in Table 4. The overall performance of the ANN is sufficient and better than that of the optimised regression model. However, ANN models with different groups of data exhibit different performance. In detail, the model with the validation group data performs the smallest RMSE, while the one with the test group data performs the greatest RMSE (22.67 compared with 29.66 kg/m^3). The reason is that the ANN model only trained based on the explored features of the training group data. The training and validation group data may contain more common features, and hence, the corresponding RMSE is smaller. On the contrary, the training and test group data may contain fewer common features, which leads to a greater corresponding RMSE. Thus, the generalisation capability of this model is bad. This is also proved by the uneven data distribution of the ANN-model-predicted density when the different groups of data are input. As can be seen from Figure 8, some of the data points are located close to or even at the fit line when the training group data are input. On the other hand, the rest of the data points are located far away from the fit line, which lowers the corresponding R^2 value to 0.85. In contrast, when the test data are input, fewer data points are located near the fit line. Therefore, the corresponding R^2 value becomes lower, only 0.81, which is insufficient. Overall, the performance of the ANN model shows that it only explores the features of parts of the data

Table 5. The performance of the hybrid model.

	R^2	RMSE (kg/m^3)
Training group	0.93	17.27
Validation group	0.90	17.04
Test group	0.92	20.13
Overall	0.92	18.31

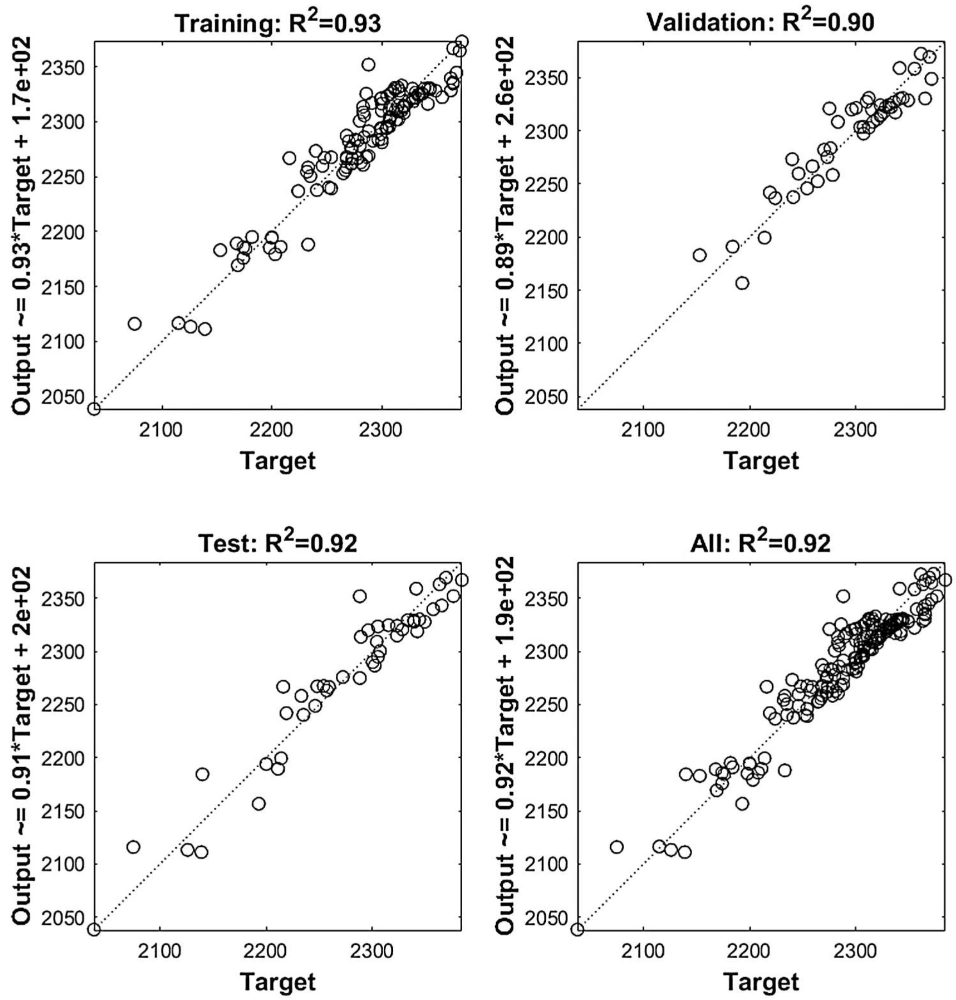

Figure 9. The performance of the hybrid model.

rather than those of all the data, resulting in its poor generalisation capability. Thus, further optimisation is required on the ANN model, and the best way is to preprocess the data before input to the ANN model.

Hence, the hybrid approach is applied, and its preprocessed approach is the nonlinear model 2, which is the optimised regression model. The performance of the hybrid model is shown in Table 5. It exhibits excellent accuracy and generalisation capability. The RMSEs of the hybrid model with the training, validation, and test group data are close to each other (17.27, 17.04, and 20.13 kg/m^3, respectively). The RMSE of the hybrid model with the test group data is slightly greater than the overall RMSE (18.31 kg/m^3). On the contrary, it is much smaller than the RMSE of the normal ANN model with test group data or that of the nonlinear model 2. It is less than a third of the original RMSE (67.98 kg/m^3) shown in Table 3. Therefore, the accuracy of the hybrid model is the best among all the models and its generalisation capability based on the RMSE results is also improved. The improvement of its generalisation capability is also proved by its even data distribution of the hybrid-model-predicted density. As shown in Figure 9, most of the data are located at an appropriate distance from the fit line no matter which group data are input. In addition, the R^2 values of the model with different group data are sufficiently high and close to each other (0.93, 0.90, and 0.92, respectively). This means that the features explored by the hybrid model are the common features of most of the data. Hence, the generalisation capability of the hybrid model is better than that of the ANN model. Overall, the hybrid model is proved to be the optimised model with the best performance among all the models.

8. Conclusion

The non-destructive device, PQI, is designed to measure the density of the asphalt pavement based on electromagnetic induction. However, the accuracy of the PQI is not sufficient since the built-in algorithm can not properly match the true density and the PQI density with respect to temperature. This paper proposes a hybrid approach combining regression and ANN models to improve the accuracy of the PQI device. The optimised regression model is used as the preprocessed approach, and the regression-model-predicted density is then used to train the ANN model. The data, including PQI density, core density, and temperature, are collected from the field tests conducted in New Zealand. The results show the effectiveness of the hybrid approach. The accuracy of the hybrid approach is better than that of the ANN model and any of the regression models. The RMSE of the hybrid model is less than a third of the original RMSE of the PQI device. In addition, the generalisation capability of the hybrid model is better than that of the ANN model. Hence, when applied in the field test, the proposed hybrid approach can significantly improve the accuracy of the PQI device by simply inputting the PQI density into the model of the approach. On the contrary, the limitation of the approach is obvious. Except for temperature, the other factors that may affect the PQI density (like moisture) are not considered in this approach. To further improve this approach, moisture data can be collected from the field tests and used to be an input for training the model in our future work.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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