Artificial Neural Network (ANN) Approach to Predict LWST Values from Friction and Texture Measurements

Mohammad Ali Khasawneh, Mohammad F. Aljarrah, and Nael Alsaleh

***Abstract*—The paper aims to find whether friction values namely skid numbers obtained by the Locked Wheel Skid Trailer (LWST) device can be predicted using values obtained by the Dynamic Friction Tester (DFT) and the Circular Texture Meter (CTM). The last two measure the coefficient of dynamic friction (called DFTx) at different speeds (labeled x) and the Mean Profile Depth (MPD), they also measure the International Friction Index (IFI) parameters F_{60} and S_p. Artificial Neural Network (ANN) software was used to investigate the relationships. Twelve (12) different models were proposed with different input parameters and the best model giving the highest coefficient of determination (R^2) was discussed in this paper. The results show that the most influential factors on LWST friction values are MPD, DFT0, DFT50, and DFT64 and MPD was the strongest among them. In addition, results show that the ANN approach is very efficient in predicting the LWST friction values for both training and validation sets with R^2 values of 79% and 83%, respectively. It was also shown that the IFI parameters were relatively less influential on LWST values than DFT and MPD measurements.**

***Index Terms*—Artificial Neural Network, prediction, LWST, DFT, CTM, IFI, friction, texture.**

I. Introduction

Pavement skid resistance is the property that plays a major role in highway design, maintenance, safety and accidents analysis [1], [2]. It is the ability of the pavement surface to prevent the loss of traction with the vehicle tire. We always aim for a pavement surface with friction that is adequate enough to prevent slipping of the vehicle, but at the same time, the surface must not be very rough to decrease tire wearing due to friction.

Many factors affect the pavement surface friction, like wetting conditions, bleeding, particles angularity, and one of the most influencing factors is the surface texture which is the feature of the road surface that relates to most tire-pavement interactions, including wet friction, noise, splash and spray, rolling resistance and tire wear [3], [4].

Pavement texture has been categorized into four ranges based on the wavelength of its components: micro-texture, macro-texture, mega-texture, and roughness or evenness. However, wet friction is influenced by the micro-texture and macrotexture range of properties [5]-[10].

Manuscript received June 17, 2021; revised August 15, 2021.

Mohammad Ali Khasawneh is with Civil Engineering, Prince Mohammad Bin Fahd University, Al Azeziya, Eastern Province, Kingdom of Saudi Arabia, on leave from Jordan University of Science and Technology, Irbid, Jordan. (Corresponding author, e-mail: mkhasawneh@pmu.edu.sa).

Mohammad F. Aljarrah and Nael Alsaleh are with Civil Engineering Department, Jordan University of Science and Technology, Irbid, Jordan (e-mail: mfaljarrah166@eng.just.edu.jo, nmalsaleh15@eng.just.edu.jo).

Different devices are used to measure friction values, such as Locked Wheel Skid Trailer (LWST), Dynamic Friction Tester (DFT) and Circular Texture Meter (CTM), British Pendulum Tester (BPT), California Skid Test (CST), etc. Our focus here will be on the first three (LWST, DFT and CTM).

Many studies have been conducted to study the correlation between different friction values obtained by different devices or to find the friction values using pavement surface characteristics. In addition, many studies have been carried out using the Artificial Neural Network (ANN) approach in pavement engineering; some of these studies are reviewed in this section.

Khasawneh and co-workers studied the correlation between LWST skid numbers at 64 km/h, DFT friction numbers at 64 km/h, DFT friction numbers at 20 km/h and MPD measured using the CTM using simple, multiple linear and nonlinear regression techniques [11]-[13]. DFT64 was used to account for macrotexture effect while DFT20 was used to account for micro-texture effect since micro-texture effect is measured using low speed friction measuring devices. Author of these studies also investigated the International Friction Index (IFI) parameters F_{60} and S_p. It was also found that the IFI parameters are good estimators in predicting LWST values. Finally, using non-linear regression had provided even better prediction power to LWST values. Along the same lines, Bustos and research group stated that the inclusion of texture measurements when estimating skid resistance values significantly enhanced the predictive power of the developed models [14].

Meegoda *et al.*, 2015 studied the correlation between skid number values obtained by LWST and the mean profile depth MPD using a vehicle mounted laser [15]. A positive correlation between Skid Number (SN) values and MPD for MPD values less than 0.75 mm was found, then there was a negative correlation as the MPD increases to 1.1 mm and beyond the MPD value of 1.1 mm to the maximum value of 1.4 mm, SN values remained almost constant.

Zahir *et al.*, 2017 used Laser Crack Measurement System (LCMS) Three-Dimensional laser profile and LWST to calculate the texture depth and the skid number and to find whether there is a correlation between them in order to use LCMS as a supplement to LWST for monitoring [16]. A good correlation between the two measurements in the range of 0.5 to 1.5mm depths was reported. Liu *et al.*, 2017 also used three-dimensional micro- and macro texture measurements using a line laser scanner [17]. Results confirmed that the relationship between 3D mean texture depth and 3D root mean square height is significant. In addition, Lu *et al.*, 1971 showed that there is a correlation between the skid number and the stopping distance, a

DOI: 10.7763/IJET.2021.V13.1191

significant one-to-one correlation was obtained [18]. Further, Fernando *et al.*, 2013 studied the relationship between skid numbers obtained by LWST and variable-slip and fixed-slip devices where a reasonable relationship was found [19].

The use of Artificial Neural Network (ANN) technique in pavement engineering and modeling is also considerable as can be seen in several relevant studies such as [20]-[22].

The LWST operates at high speeds and interferes with traffic and consequently requires quite long time, unlike the DFT and CTM, which can be used at low operating speeds and less traffic interruptions and time. Therefore, it becomes handy to use the values obtained by the DFT and CTM devices to predict LWST friction values. Furthermore, since the DFT and CTM devices are used to calculate the IFI parameters (F_{60} and S_p); it is intended to use these values predict the LWST measurements to explore the presence of any potential correlation. In this study, ANN approach was utilized.

II. Methodology

The data was collected using actual pavement sections in five (5) different locations in the state of Ohio. Along the left wheel path two runs were made and the average of the two runs was recorded. Data was collected at the same time of the year to decrease the environmental and traffic effects and for two consecutive years. Also lack of skid resistance in the collected data could be due to the time data was taken in the summer, which might have caused bleeding of asphalt, so friction values could be lower than expected [13]. The three devices used for this task are the LWST as per ASTM E-274 [23], DFT as per ASTM E-1911 [24] and CTM in accordance with ASTM E-2157 [25]. IFI values were also computed based on friction and texture measurements. In this study, the ANN software called Visual Gene Developer was used. Besides, IFI parameters S_p and F_{60} were utilized to predict LWST friction values. A comparison was made between different ANN networks and another set of comparisons with previously developed statistical models [13] were carried out as well.

The experience of using ANN analysis in transportation-related studies is extracted from Semeida. In his research, the Multilayer Perceptron (MLP) neural network models provided the best performance of all models. In addition, due to the variety in available learning algorithms, this network is usually preferred in engineering applications. Moreover, hyperbolic tangent and sigmoidal functions are the most commonly used transfer functions in ANN applications [26], [27]. Many trials were run to confirm that the hyperbolic tangent and sigmoidal functions are the most suitable transfer functions for this study. Keep in mind that the major difference between these two functions is the range they cover; the hyperbolic tangent range is from zero to one whereas the range of sigmoidal function is from minus one to one.

III. Results and Discussion

Visual Gene Developer as an ANN program was used for the prediction of LWST measurements using different combinations of DFT, MPD, and IFI parameters (F_{60} and S_p). In this study twelve (12) models were generated using different combinations and analysis parameters. Results are summarized in Fig. 1.

In general, ANN consists of three layers, namely, the input, the hidden, and the output layers. In statistical terms, the input layer contains the independent variables and the output layer contains the dependent variables. ANN typically starts out with randomized weights for all their neurons. When a satisfactory level of performance is reached, the training is ended and the network uses these weights to make a decision. The neural network computing system is made up of a number of simple and highly interconnected nodes or processing elements called neurons.

Among the different kinds of transfer functions that can be used, a hyperbolic tangent and sigmoidal functions were adopted in this study.

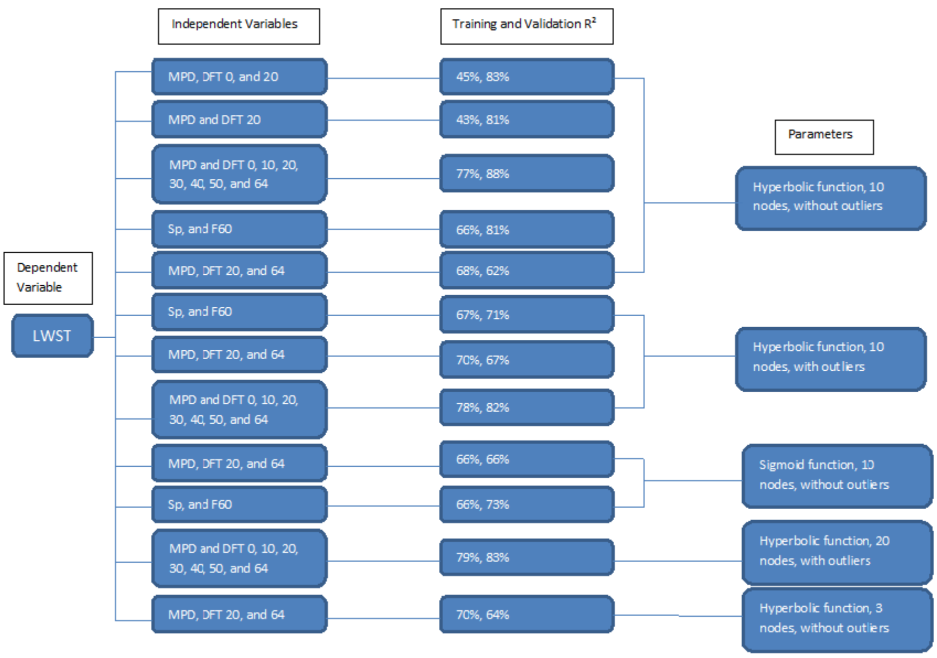

Fig. 1. ANN results summary.

As shown in Fig. 1, the highest coefficient of determination (R^2) was obtained when using MPD, DFT0, DFT10, DFT20, DFT30, DFT40, DFT50, and DFT64 as independent variables. It is worthy to be mentioned here that the numbers following the abbreviation DFT represent the speed at which friction was recorded. This model was developed using hyperbolic tangent transfer function while outliers are kept and twenty (20) nodes in the hidden layer were used. This resulted in R^2 of 79%.

The dataset consists of one hundred and seventy-four (174) LWST values and was divided into a training dataset and a validation dataset. The training dataset consisted of 90% of the sample size and the validation dataset had the remaining10 %. Model performance measures are Summation of Error (SoE), average error per single data output and R^2 for both training and validation datasets.

Numerous trials were performed to reach the proper percentage between training and testing datasets that provide the best performance in predicting LWST as the dependent variable. The architecture of the ANN model structure is shown in Fig. 2 below.

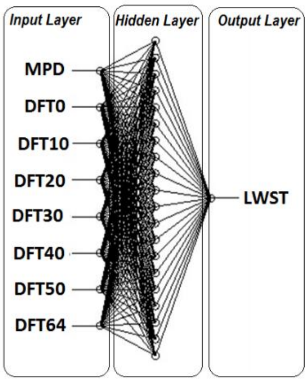

Fig. 2. Architecture of the ANN.

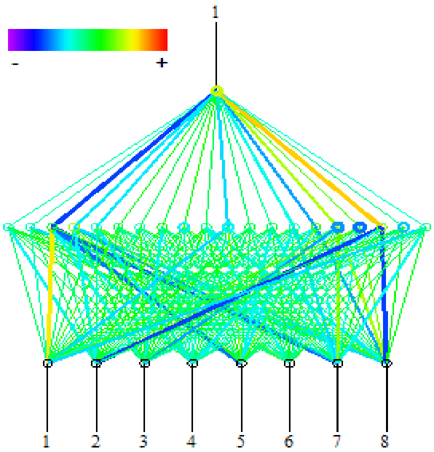

Fig. 3. Analyzed network diagram.

The results from the ANN analysis include the analysis of the architecture of the ANN structure in terms of the weights since Visual Gene Developer, the adopted software used in the analysis, provides graphical visualization of trained network. In the analyzed network diagram in Fig. 3, lines represent weight factors and circles (nodes) indicate threshold values. Thus, the color is a function of the weight factor in terms of its direction while the line width represents the magnitude of the weight factors, in other terms, it is the absolute weight factor multiplied by two.

It can be noticed from Fig. 3 that the most influencing factors on LWST values are MPD, DFT0, DFT30, DFT50, and DFT64 based on the line color, while MPD, DFT0, and DFT64 are the most influential based on the line width.

As can be observed from the ternary map shown in Fig. 4, the most influencing factor is the MPD, which is plotted as the third variable. The ternary map indicates that the higher normalized value of the MPD leads to higher values of the LWST. In addition, the effect of the other two variables (DFT0 and DFT64) is quite marginal with a slight preference for the first variable up to a certain extent. Hence, it can be noticed from the ternary map that the inclination of higher predicted LWST friction values is toward the higher values of normalized DFT64 variable, which is plotted as a second variable in the above ternary prediction map.

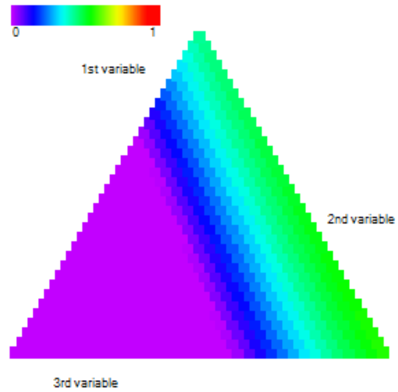

Fig. 4. ANN ternary map.

The analysis results showed a significant enhancement over all of the performance measures indicators compared with the regression analysis outcomes. The observed R^2 values for both training and validation datasets were 79% and 83%, respectively, whereas the summation of the errors and the average error for the normalized training set were 0.379 and 0.0021, respectively. The interception and slope degrees are shown in Table I. The relationships between training and validation actual and predicted data are shown in Fig. 5 and Fig. 6, respectively.

TABLE I: TRAINING AND VALIDATION SETS REGRESSION ANALYSIS RESULTS

Category	Variable	Coefficient of Determination (R^2)	Slope	y-intercept
Training	Out 1	0.79	0.78	0.15
Validation	Out 1	0.83	0.86	0.09

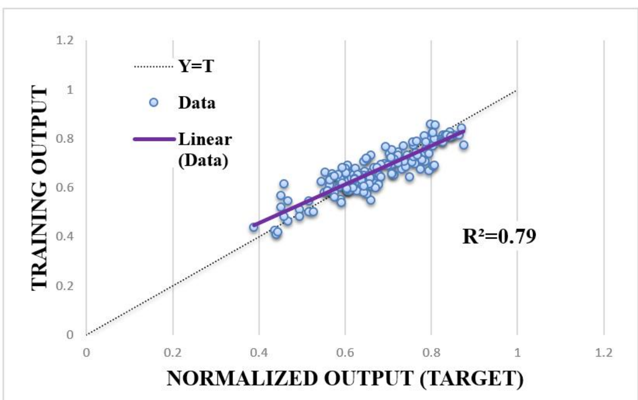

Fig. 5. Training actual vs. predicted data.

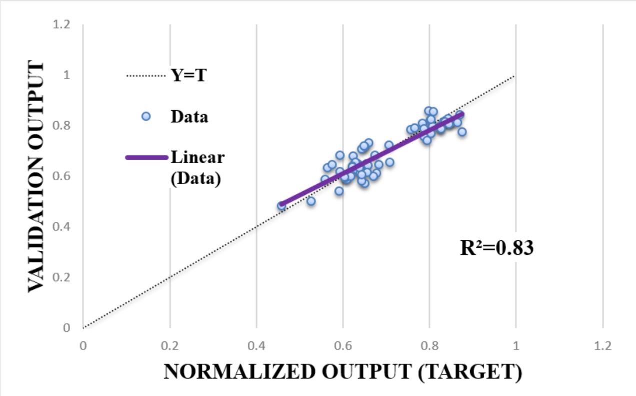

Fig. 6. Validation actual vs. predicted data.

Overfitting represents the difference between the training and validation coefficient of determination (R^2). Overfitting has two major types as shown in Fig. 7. The first type is called "strong overfitting", which occurs when the difference in R^2 exceeds 10%. The second type is called "little overfitting", which occurs when the difference is less than 10%. Strong overfitting can be solved by collecting more data, and increasing the number of independent variables (meaning the model capacity is not high enough). In this study, the strong overfitting problem was found in three models and was solved by using eight (8) independent variables together.

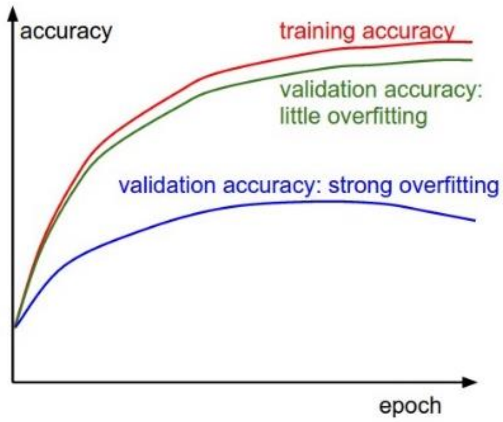

Fig. 7. Overfitting types.

IV. Conclusion

Based on the ANN results obtained in this study, the following conclusions can be made:

1) The most influential factors on LWST friction values are MPD, DFT0, DFT30, DFT50, and DFT64.

2) The ANN modeling provided better results than conventional regression modeling.

3) ANN analysis concluded that MPD has the highest influence on the values of LWST followed by DFT64.

4) In this study, there is no difference between the results obtained using the hyperbolic and sigmoidal transfer functions.

5) Increasing number of nodes in the hidden layer leads to an increase in the overall accuracy of the predicted values and the overall R^2 of the model.

6) The use of DFT and MPD values to predict LWST friction values was more significant than the use of the IFI parameters (F_{60} and S_p).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

MAK conducted the data compilation, set the study layout and reviewed and wrote the final version of the paper; MFA conducted the literature review and helped write the draft version of the paper; NA analyzed the data and helped write the draft version of the paper; all authors had approved the final version.

References

[1] N. I. Shbeeb, M. A. Khasawneh, and A. A. Al-Omari, "The development of a predictive tool to reduce experimentation time for the polishing and frictional evaluation of asphalt pavement surfaces," *Construction and Building Materials*, vol. 186, pp. 740-750, 2018.

[2] M. A. Khasawneh, "Laboratory study on the frictional properties of HMA specimens using a newly developed asphalt polisher," *International Journal of Civil Engineering*, vol. 15, no. 7, pp. 1007-1017, 2017.

[3] M. Khasawneh, M. Smadi, and H. Zelelew, "Investigation of the factors influencing wavelet-based macrotexture values for HMA pavements," *Road Materials and Pavement Design*, vol. 17, no. 3, pp. 779-791, 2016.

[4] J. J. Henry, *Evaluation of Pavement Friction Characteristics*, Transportation Research Board, 2000.

[5] M. A. Khasawneh and M. A. Alsheyab, "Effect of nominal maximum aggregate size and aggregate gradation on the surface frictional properties of hot mix asphalt mixtures," *Construction and Building Materials*, 244, pp. 1-10, 2020.

[6] M. A. Khasawneh, N. I. Shbeeb, and A. A. Al-Omari, "Analytical tool to shorten polishing time based on Mean Texture Depth (MTD) of flexible pavements," *Road Materials and Pavement Design*, vol. 21, no. 3, pp. 737-756, 2020.

[7] M. A. Khasawneh, "Macrotexture characterisation of laboratory-compacted hot-mix asphalt specimens using a new asphalt polishing machine," *Road Materials and Pavement Design*, vol. 19, no. 2, pp. 400-416, 2018.

[8] H. Zelelew, M. Khasawneh, and A. Abbas, "Wavelet-Based characterisation of asphalt pavement surface macro-texture," *Road Materials and Pavement Design*, vol. 15, no. 3, pp. 622-641, 2014.

[9] D. Wilson and R. Dunn, "Polishing aggregates to equilibrium skid resistance," *Road & Transport Research Journal*, vol. 14, no. 2, pp. 55-71, 2005.

[10] S. Goodman, Y. Hassan, and A. E. Halim, "Preliminary estimation of asphalt pavement frictional properties from superpave gyratory specimens and mix parameters," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 173-180, 2006.

[11] M. A. Khasawneh, "The development and verification of a new accelerated polishing machine," doctoral dissertation, University of Akron, 2008.

[12] M. A. Khasawneh and R. Y. Liang, "Correlation study between locked-wheel skid trailer and dynamic friction tester," in *Proc. Transportation Research Board 87th Annual Meeting*, 2008.

[13] M. Khasawneh, "The prediction of LWST values from DFT and CTM measurements using linear and nonlinear regression analyses," *Jordan Journal of Civil Engineering*, vol. 9, no. 4, pp. 487-498, 2015.

[14] M. Bustos, T. Echaveguren, H. D. Solminihac, and A. Caroca, "Development of correlation equations between different measurements of skid resistance in pavements," *Indian Journal of Engineering and Materials Sciences*, vol. 13, no. 1, pp. 117-122, 2006.

[15] J. N. Meegoda and S. Gao, "Evaluation of pavement skid resistance using high speed texture measurement," *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 2, no. 6, pp. 382-390, 2015.

[16] H. Zahir, M. Hossain, S. Islam, and R. Miller, "Road surface texture evaluation using 3-D laser data," in *Proc. Transportation Research Board 96th Annual Meeting*, 2017.

[17] Q. Liu, S. L. Tighe, and A. Shalaby, "Assessment of airfield runway macrotexture and friction using three-dimensional laser-based

measurements," in *Proc. Transportation Research Board 96th Annual Meeting*, 2017.
[18] Q. Lu and B. Steven, "Friction testing of pavement preservation treatments: Literature review," Compare, 1971.
[19] E. Fernando, R. Zimmer, and M. Mikhail, "Comparative evaluation of locked-wheel and fixed-slip skid systems," *Transportation Research Record: Journal of the Transportation Research Board*, no. 2369, pp. 125-134, 2013.
[20] S. Najafi, G. W. Flintsch, and S. Khaleghian, "Pavement friction management – artificial neural network approach," *International Journal of Pavement Engineering*, vol. 20, no. 2, pp. 125-135, 2016.
[21] N. Zavrtanik, J. Prosen, M. Tušar, and G. Turk, "The use of artificial neural networks for modeling air void content in aggregate mixture," *Automation in Construction*, vol. 63, pp. 155-161, 2016.
[22] J. Gajewski and T. Sadowski, "Sensitivity analysis of crack propagation in pavement bituminous layered structures using a hybrid system integrating artificial neural networks and finite element method," *Computational Materials Science*, vol. 82, pp. 114-117, 2014.
[23] American Society for Testing and Materials, "Skid resistant of paved surfaces using a full-scale tire," ASMT Standard Test Method E 274-97, Book of ASTM Standards, Volume 04.03, Philadelphia, PA, 2005.
[24] American Society for Testing and Materials, "Measuring pavement surface frictional properties using the dynamic friction tester," ASMT Standard Test Method E 1911-98 (2002), Book of ASTM Standards, Volume 04.03, Philadelphia, PA, 2005.
[25] American Society for Testing and Materials, "Standard test method for measuring pavement macrotexture properties using the circular track meter," ASTM Standard Test Method E-2157-01, Book of ASTM Standards, Volume 04.03, Philadelphia, PA, 2005.
[26] A. M. Semeida, "Impact of highway geometry and posted speed on operating speed at multi-lane highways in Egypt," *Journal of Advanced Research*, vol. 4, no. 6, pp. 515-523, 2013.
[27] A. M. Semeida, "New models to evaluate the level of service and capacity for rural multi-lane highways in Egypt," *Alexandria Engineering Journal*, vol. 52, no. 3, pp. 455-466, 2013.

Mohammad Ali Khasawneh was born in Jordan on August 17th 1980. Dr. Khasawneh has M.Sc. and Ph.D. degrees in civil engineering from the University of Akron, Ohio, USA in the years 2005 and 2008, respectively, and B.Sc. degree in civil engineering from Jordan University of Science and Technology (JUST) in 2003. He is an Associate Professor of civil engineering at Prince Mohammad Bin Fahd University (PMU), Kingdom of Saudi Arabia. His research interests include highway materials and he is interested in educational technology research and development.

Dr. Khasawneh is a graduate of the Excellence in Civil Engineering Education (ExCEEd) program. He is a member of the American Society of Civil Engineers (ASCE), Institute of Transportation Engineers (ITE), American Society of Engineering Education (ASEE) and Jordan Engineers Association (JEA).

Mohammad Fuad Aljarrah was born in Jordan on March 1st, 1992. Mr. Aljarrah has M.Sc. and B.Sc. degrees in civil engineering from Jordan University of Science and Technology (JUST) in the years 2018, and 2015, respectively. He is a PhD student in civil engineering at Texas A&M University (TAMU), Texas, USA. His research interests include highway materials, specializing in nanoscale characterization and modelling of asphalt binders. He is also interested in artificial intelligence and its application in materials engineering.

Mr. Aljarrah is a member of the Academy of Pavement Science and Engineering (APSE), and Jordan Engineers Association (JEA).

Nael Alsaleh was born in Jordan on July 30th, 1993. Alsaleh is a Ph.D. candidate in Transportation Engineering at the Laboratory of Innovations in Transportation (LiTrans), Ryerson University, Ontario, Canada. He completed a B.Sc. in Civil Engineering in 2015 and a M.Sc. in Transportation Engineering in 2017, both from Jordan University of Science and Technology (JUST), Jordan. Alsaleh started his Ph.D. in September 2019, and his research interests include on-demand shared mobility services, transportation systems simulation, as well as connected and autonomous vehicles. He is a member of the Institute of Transportation Engineers (ITE) and Jordan Engineers Association (JEA).