Artificial Neural Network Analysis of Factors Influencing Canadian Power Engineering Advanced Certification

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***Abstract*—This paper provides additional insight into Canadian Power Engineer's advancement intention through the mechanism of complementary artificial neural network (ANN) analysis. An original 2018 dissertation investigated the knowledge gap concerning factors influencing Canadian power engineers' decision to pursue advanced certification in the Canadian provinces of British Columbia and Alberta. The dissertation employed correlational, multiple linear regression (MLR), and ordinal logistic regression (OLR) analysis. The focus of the current paper is to compare the 2018 MLR and OLR methods and results, with artificial neural network (ANN) analysis using the same 2018 power engineering dissertation dataset. Moving forward the original dataset used for the 2018 dissertation study is referenced as the 'power engineering dataset.' The original 2018 analytical results obtained through MLR and OLR analyses are compared with the results of the 2020 ANN applications of multiplayer perceptron (MLP) and radial basis function (RBF). Specifically, standard regression is evaluated against ANN regression methods. The original dissertation found that the independent variables (IVs) of time commitment, responsibility, and elapsed time significantly influenced the dependent variable (DV) of advancement intention. The three remaining IVs that did not exhibit significant relationships with the DV were educational support, peer appraisal, and locus of control (LOC). ANN analysis generated comparable results to those obtained in the original dissertation study. The multilayer perceptron (MLP) and radial basis function (RBF) applications denoted that time commitment (TIME) had the greatest importance concerning outcome prediction, followed by responsibility (RESP), elapsed time (ELAPSED), education (EDUC), peer appraisal (PEER), and locus of control (LOC). The comparative quantitative analysis provided objective empiricism regarding factors influencing certification advancement, while implicitly recognizing the human-based qualitative roots of decision-making.**

Keywords*—*Canadian power engineering, regression, artificial neural networks, machine learning, complementary analysis

I. Introduction

Complementary ANN analysis was conducted in 2020 on the power engineering dataset generated for the original 2018 dissertation titled: Factors Influencing Canadian Power Engineers' Decision to Pursue Advanced Certification [1]. ANN analytical results were compared with the original 2018 dissertation regression results. The studys' dual purpose was to: (a) compare standard regression and ANN methods; and (b) to retest the original data.

Power engineering certification in Canada comprises a hierarchical, graduated system available to candidates of all ages. The 2018 dissertation offered insight into the knowledge gap related to factors influencing Canadian power engineers' decision to pursue advanced certification. The purpose of the study was to investigate potential variable relationships between power engineers' intent to upgrade to advanced certification levels (DV), and factors influencing the advancement decision (IVs). The original research methodology comprised a quantitative correlational design, in which linear and logistic regressions employing a modified Bonferroni equivalent alpha were utilized. This quantitative approach was chosen to provide a broader view of the phenomena under investigation [2,3]. The results revealed positive, statistically significant relationships between the DV of advancement intention and three of the six IVs. The variables of time commitment, responsibility, and elapsed time exerted statistically significant effects on advancement intention (DV). The three remaining IVs that did not exhibit significant relationships with the DV were educational support, LOC, and peer appraisal. This indicated that the IVs of educational support, LOC, and peer appraisal did not significantly influence the DV when compared to the significant influences of time commitment, responsibility, and elapsed time on the DV. Comprehension of the influential factors on the intention of Canadian power engineers to pursue advanced certification furnishes industry and academia with insight into the barriers and enablers and the correlation of decision factors, with advancement intention. Comparative analyses employing ANN methods provide additional insight and greater comprehensive assessment.

A. *Study Population (Original Study)*

The population comprising the power engineering dataset consisted of Canadian certified power engineers working primarily in registered First-Class facilities in British Columbia and Alberta [4]. The study population of First, Second, and Third-Class engineers [5] was estimated at 4,700 at the time of data collection. The total population figure was difficult to confirm since once an individual attained certification, this certification was seldom re-registered. Since the original study, a formalized re-registration process initiated in 2019 is currently operating [4].

B. *Sample (Original Study)*

Initially, a target sample size of a minimum of 150 participants was approximated for the main study. The figure was established through a priori power analyses. A priori power analyses were conducted in G*Power 3.1.9.2 specifying a correlation and assuming a bivariate normal model was used. A priori analyses are performed before a study is conducted to determine sample size and to control statistical power [6,7]. Additional specifications consisted of a one-tailed test, an alpha of 0.05, a minimum statistical power of 0.80, a weak correlation of 0.2, along with a null hypothesis of zero correlation [8]. The a priori analysis specified a minimum sample size of 153 to achieve a minimum statistical power of 0.80. The initial estimated attainable sample was approximately 440. The survey generated 338 responses from the sample of 440, resulting in a 77% response rate. The 338 initial survey responses were then reduced to 298 due to missing or incomplete information.

C. *Original Survey*

An existing, adaptable survey could not be located for use in the original power engineering study. Consequently, an original five-point Likert-type ordinal-level survey was developed to collect and analyze numerical data. A survey instrument was deemed as the most appropriate data collection tool for the quantification of subjective variables for correlational analysis [9]. Likert-type questions provide specific information, with the scale being insensitive to linear transformation. The survey was implemented using Survey Monkey™, which is a commercially available site. The survey contained original questions coupled with several peer-reviewed locus of control survey questions extracted with permissions from an existing validated survey [10]. Locus of control questions were integrated with the original survey questions to form a single survey. The original survey questions were conceptualized in accordance with the research questions and hypotheses. The 23-question original survey contained one question for the DV of advancement intention. The IVs were represented by the following number of survey questions: (a) time commitment (4 questions); (b) educational support (4 questions); (c) locus of control (3 questions); (d) elapsed time (4 questions); (e) responsibility (3 questions); and (f) peer appraisal (4 questions). Note that responses to the individual questions for each IV were to reduce the overall number of tests required in the analysis.

The survey instrument was pilot-tested antecedent to data collection for the main study. Pilot testing consisted of three elements: (a) construct validity testing via factor analysis; (b) reliability testing (internal consistency) using Cronbach's alpha; (c) and content validity testing using Lawshe's CVR [11,12,13]. G*Power, as in the main study, was employed to determine the appropriate pilot study sample size for pilot testing the data collection instrument (survey). The a priori power analysis indicated a sample size of approximately 30 for the pilot study. The results of the pilot study revealed an acceptable factor structure for construct validity, as per the rotated component matrix of 0.803 to 0.913 [14]. In terms of reliability, Cronbach's alpha values exceeded 0.7 and were deemed acceptable [13]. The computed Lawshe's CVR for the pilot study was 0.92, which exceeded the acceptable threshold value of 0.56 [12]. Pilot study data was downloaded directly from the Survey Monkey™ database into a Statistical Product and Service Solutions (SPSS v24) data file and analyzed using SPSS software. The results of pilot testing confirmed that the survey instrument was appropriate for use in the main study. The data for the pilot study were not included in the data used for the main study.

Individual participant protections were observed, with collected data treated as undifferentiated to protect the organizations identity and to avoid unsolicited exposure. Data collection was conducted in a non-interventional manner without manipulating the IVs or disturbing the power engineering population. The Informed Consent form was embedded in the electronic survey. Data was collected electronically via a survey link emailed to each contact agent at each participating facility. The contact agent then emailed the link to all First, Second, and Third-Class Power Engineers at their facility for collection of electronic responses.

D. *Correlational and Regression Analysis (Original Study)*

The objective of the original analysis was to determine the existence of statistically significant relationships between advancement intention (DV) and factors influencing advancement intention (IVs). Statistical analysis in the original dissertation [1] utilized correlational analysis employing Spearman's rho and MLR to generate multiple correlational values, and ordinal (ordered) logistic regression (OLR) using a modified Bonferroni equivalent alpha. Spearman's rho tested the null hypotheses to determine if specific decision factors corresponded with advancement intention (DV). The Spearman's rho correlative measure was suitable for analyzing data that are not interval-level to assesses covariance between two variables [2,3]. Correlation and MLR were followed with OLR to generate odds ratios and to identify if advancement intention fluctuated with decision factors. OLR is appropriate in cases where the DV is an ordinal variable, and when the research objective is to determine the extent to which one or more predictors affect this ordinal DV [15,16,17]. The research design aligned with the study objectives of determining the presence or absence of correlations between advancement intention and decision factors influencing advancement intention. Study weaknesses were potentially related to the less robust nonprobability (non-random) convenience sampling method [18], and a smaller sample size limiting the potential to detect true relationships among the study variables [19].

E. ***Correlational and Regression Analysis Results (Original Study)***

Likert-type scale responses were coded from (strongly agree = 1) to (strongly disagree = 5) before uploading the response data to the SPSS data file. The data was coded in this manner so that SPSS comparisons could be made with 'strongly disagree' as the base category. OLR allows SPSS to make comparisons with the highest coded (numbered) category as the base category. In the data analysis stage, Spearman's rho evaluated the degree to which the relationship between two variables can be explained via a monotonic function. OLR was selected to follow Spearman's rho to add methodological strength to the analysis. Spearman's rho tested for the existence, magnitude, and direction of the relationship between two non-normally distributed measures making this test an appropriate choice for the current study [2]. Ordinal-level measurement aligns with Likert-type scales, Spearman's rho, and OLR analysis. The summative benefit of following Spearman's rho with OLR methodology is that the impact of each IV on the DV is determined through OLR while controlling for all other IVs included in the analysis [15,16,17]. Following Spearman's rho and MLR with OLR provided the researcher with correlation values and odds ratios as composite tools for the evaluation of the research hypotheses.

In conjunction with OLR, a modified Bonferroni equivalent -α of 0.0083 was calculated to manage Type-1 error in the original study. The objective of the modified Bonferroni adjustment was to make it difficult for a single test to be more statistically significant than another test [20,21,22]. Consequently, the modified Bonferroni equivalent alpha was generated to account for cumulative error resulting from myriad statistical tests in the study. These numerous tests used the same database with the Bonferroni equivalent -α calculated at 0.0083. To obtain statistical significance for any one test, the Bonferroni adjusted level of significance had to be less than or equal to 0.0083. A probability value of less than 0.0083 for a single test would be deemed statistically significant. Conversely, a test statistic would be deemed non-significant if it resulted in a probability value greater than 0.0083.

TABLE I. SUMMARY – *MLR AND OLR*

	Multiple Linear Regression (MLR)			Ordinal Logistic Regression (OLR)						
				95% confidence interval[1]				95% confidence interval[2]		
Variable	r	r^2	Sig (p-value)	Lower Bound	Upper Bound	Exp_B	Wald $\chi^2(1)$	Lower Bound	Upper Bound	Sig (p-value)
Time commitment	0.70	**0.49**	< .001	1.141	1.878	4.524	64.357	3.129	6.542	< .001
Responsibility	0.52	**0.27**	< .001	0.383	1.426	2.471	11.554	1.467	4.163	0.001
Time Elapsed	0.50	**0.25**	< .001	-1.489	-0.652	0.343	25.178	0.226	0.521	< .001
Educational support	0.41	0.17	< .001	-0.62	0.298	0.851	0.473	0.538	1.347	0.492
Locus of control	0.18	0.03	0.054	-0.686	0.062	0.732	2.675	0.503	1.064	0.102
Peer appraisal	0.34	0.12	< .001	-0.19	0.826	1.374	1.503	0.827	2.284	0.22

R-squared (r^2) values for time commitment (TIME), responsibility (RESP), and elapsed time (ELAPSED) were .49, .27, and .25 respectively (Table I). Statistically significant results for time-based variables (time commitment and time elapsed) were anticipated and intuitive. Statistically significant results for responsibility, while intuitive, were less predictable as personal predispositions toward responsibility vary. The lack of a statistically significant effect for the locus of control construct on the DV was surprising given presumed behavioral (introversion/extroversion) influences on decision-making.

II. ANN (COMPLEMENTARY STUDY)

Artificial neural networks (ANNs) are designed in alignment with the process architecture of the biological brain and nervous system. The constructed network is essentially a mathematical abstraction of the organic neural system arrangement. ANNs may be utilized in situations involving relationships between IVs (explanatory input variables) and DVs (response output variables), and where objectives involving modeling, prediction, classification, and pattern recognition are desired (23,24,25,26]. ANN and standard regression analysis share similarities in their approach to testing variable relationships. Consequently, ANN was chosen to analyze the power engineering dataset, previously analyzed using MLR and OLR. Conceptual relationships to white-box and black-box models [27,28,29] were contemplated in accordance with ANN and standard regression, respectively.

A. ***MLR***

Petek Šter, Švab, and Šter (2015) [26] found that ANNs may possess a greater capacity to detect complex input-output relationships between IVs and DVs than their standard regression equivalents. However, the performance of an ANN model is contingent upon network configuration, researcher experience, and choice of variables [30,31]. Relationships between variables exist in linear or nonlinear formats. Consequently, ANNs are useful for extracting the authentic nature of these relationships [23,26]. MLR is utilized to investigate the relative effect of multiple IVs on a specific DV with minimization of differences between observed and predicted values [32,33,34,35]. MLR is popular as a standard regression statistical approach but often characterized as less robust as it can be biased by influential outliers. Trade-offs among standard regression methods and ANNs are often subject to re-evaluation when considering methodological limitations and forecasting accuracy [30,36]. Accordingly, researchers must be judicious when endeavoring to draw comparisons between analytical methods.

B. OLR

OLR, as a comparator to ANN, provides concurrent analysis of multiple IVs, while moderating the influence of confounding or intervening variables. Logistic regression methods are efficient and powerful mechanisms for evaluating IV influences or contributions to a binary outcome. OLR is well suited for assessing relationships among one or more IVs and a dichotomous outcome [37]. OLR benefits are contingent upon adopting an appropriate strategy for model development, the precise selection of variables, ensuring OLR assumptions are met, and performing an accurate validation of model outputs [38,26].

ANNs can enhance the predictive capacities of conventional statistical methods such as MLR and OLR. This complementary capacity is rooted in the ANN structure consisting of myriad interconnected neurons (units). This neuronal network forms an intricate input-output relationship where network complexity is proportional to the size of the network, and relative to the number of internal or hidden neurons comprising the network. ANNs consist fundamentally of one input layer, one or more hidden layers, and one output layer. A training process underscores ANNs' ability to adapt free parameters for input-output mapping [23,25,26]. The power engineering dataset variables are the Likert-type scale survey response values for the IVs and the DV of advancement intention. The multilayer perceptron (MLP) network was chosen for training of the model utilizing the backpropagation algorithm in SPSSv25. The radial basis function (RBF) network was also employed in the secondary analysis of the power engineering dataset. Both the MLP and RBF applications were used as comparators to the original dissertation results.

C. Complementary ANN Analysis

The primary focus of comparative analysis between standard regression and ANN regression was to determine the relative ranking of the predictors' influence on the response variable. Supplemental analysis was further employed to illustrate differentiating and complementary elements among standard regression methods and ANN regression. Creating an ANN predictive model served to investigate the comparative accuracy between the predictive capacities of standard regression and ANN [23,34]. As indicated supra, preparatory evaluations, including assumption checks for distribution normality were performed prior to testing the original power engineering dataset with correlation, regression and OLR. The assumption evaluations were not repeated prior to ANN modeling to preserve consistency for direct comparison of ANN with regression results derived from the same dataset. ANNs will accommodate a great number of variables without the rigid requirement for specific assumptions such as normality [38]. OLR and ANN are comparable for determining relationships between variables but are differentiated by factors such as ANN's learning and training functions.

A network that is trained comprises pooled regulations. These pooled features are represented by allocated weights between the neurons [39]. This distinguishing aspect provides ANNs with the ability to forecast cases not yet submitted to the network through the process of generalization. ANNs can model complex variable relationships in the absence of a priori knowledge of a model [30,31,38,35]. The ANN applications utilized for complementary analysis were: (a) multilayer perceptron (MLP); and (b) radial basis function (RBF).

D. Multilayer Perceptron (MLP)

MLP is used pervasively for generating ANN models. Akin to general ANN structure, MLP comprises one or more hidden layers between the input and output layers. Neurons are structurally arranged in layers with direct interlinked connections extending from the lower to the upper layers. Neurons existing in the same layer, or plane, are not interconnected [39,31,40,25,35]. The MLP application is the most extensively used ANN application utilizing the backpropagation algorithm [41,26]. Applications such as MLP and RBF comprise a single DV with two or more IVs, notwithstanding the magnitude or dimension of the research problem. Results provided from these types of ANN applications are differentiable and exist in a closed analytic form [42]. RBF differs from MLP in aspects such as the requirement for additional training vectors, the number of artificial neurons in the hidden layer, and in the production of bias values.

E. Radial Basis Function (RBF)

RBF is a feedforward neural network, as opposed to the MLP backpropagation algorithm described supra. The RBF arrangement comprises an input layer, a hidden layer, and an output layer. Calculation does not occur within the input layer nodes. Input layer data is forwarded only to the hidden layer. Functionally, the input layer corresponds to network inputs, the hidden layer contains several non-linear activation units, and the output layer corresponds to final network outputs. RBF training processes are termed clustering or competitive learning. As input enters the network, generation of a vector commences with calculation of distances between input and weight vectors. A final vector product is achieved through multiplication of these calculated values by bias values. Subsequently, these values proportionally generate as many neurons as there are inputs related to their corresponding functions. The output layer provides the output values [31,40]. Both MLP and RBF were included in secondary analysis of the power engineering dataset for fulsome comparison of results.

III. RESULTS (ANN COMPLEMENTARY ANALYSIS)

A. MLP Network

The Case Processing Summary table (Table II) depicts sample sizes and response percentages associated with training and testing samples. The SPSS syntax specified a 70/30 split between training and testing. The actual split comprised 208 cases (69.8%) for the training sample and 90 cases (30.2%)

for the testing sample. The neural model is trained using the training sample and tested on the remaining ~30% as a method of validating and testing the predictive accuracy of the neural network.

TABLE II. *MLP CASE PROCESSING SUMMARY*

Case Processing Summary

		N	Percent
Sample	Training	208	69.8%
	Testing	90	30.2%
Valid		298	100.0%
Excluded		0	
Total		298	

The Network Information output (Table III) and Layer Activation graphic (Fig. 1) data provide information concerning neural layer relationships. Graphically, the layer activation function diagrammatically represents the neural network paths and synaptic weights. The interconnecting lines (Fig. 1) identify linkages between the predictors (6) in the input layer, the neurons (3) in the hidden layer, and the outcome layer consisting of Likert-type response categories (5) for certification upgrade. Neural pathways (blue lines) represent negative synaptic weights. Conversely, gray lines represent positive synaptic weights. Synaptic weight pathways are conceptually analogous to positive and negative regression coefficients, albeit with greater complexity given the middle layer of artificial neurons. The thickness of the pathway is proportional to the magnitude of the synaptic weights. Thicker lines represent larger magnitudes.

TABLE III. *MLP NETWORK INFORMATION*

Network Information

Input Layer	Covariates	1	Time Commitment
		2	Elapsed Time
		3	Peer Appraisal
		4	Locus of Control
		5	Responsibility
		6	Educational Support
	Number of Units[a]		6
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Certification Advancement Intention
	Number of Units		5
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

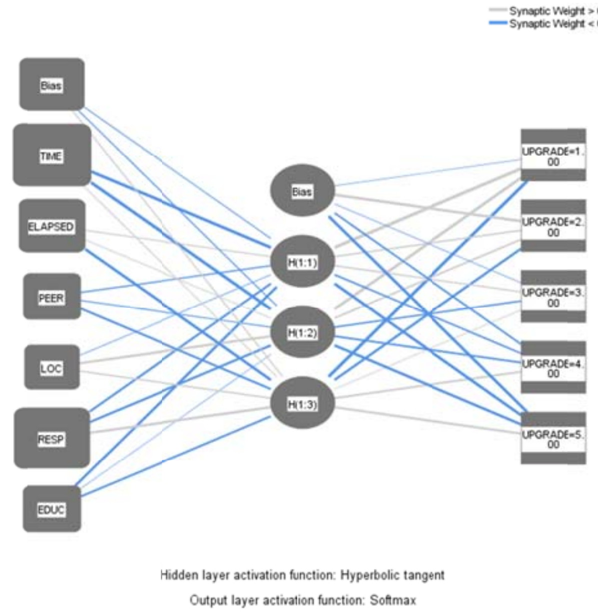

Fig. 1. MLP Layer Activation

The Model Summary output (Table IV) presents statistics related to the performance of this neural network. In the training sample, 49.0% of predictions were characterized as incorrect predictions. The testing sample comprised a higher proportion of incorrect predictions at 66.7%.

TABLE IV. *MLP MODEL SUMMARY*

Model Summary

Training	Cross Entropy Error	257.739
	Percent Incorrect Predictions	49.0%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.05
Testing	Cross Entropy Error	124.977
	Percent Incorrect Predictions	66.7%

Dependent Variable: Certification Advancement Intention
a. Error computations are based on the testing sample.

The Parameter Estimates output (Table V) present the synaptic weights associated with the neural network. The synaptic weights are a reference point in relation to the ANN diagram. The positive and negative synaptic weights correspond, respectively, to the gray and blue pathway lines in the layer activation graphic (Fig. 1). Synaptic weights may be used to calculate predicted values for the five outcomes in the output layer. Synaptic weights are associated with each of the artificial neurons. Consequently, these values must be incorporated into the equation for the predicted values associated with each of the five outcomes.

TABLE V. *MLP PARAMETER ESTIMATES*

Parameter Estimates

		Predicted							
		Hidden Layer 1			Output Layer				
Predictor		H(1:1)	H(1:2)	H(1:3)	[UPGRADE=1.00]	[UPGRADE=2.00]	[UPGRADE=3.00]	[UPGRADE=4.00]	[UPGRADE=5.00]
Input Layer	(Bias)	-.090	-.156	.166					
	TIME	-.999	-1.039	.113					
	ELAPSED	.161	.080	-.634					
	PEER	-.187	-.137	-.387					
	LOC	-.078	.458	.222					
	RESP	-.387	-.433	.476					
	EDUC	-.482	-.016	-.382					
Hidden Layer 1	(Bias)				-.030	.629	-.060	-.256	-.690
	H(1:1)				1.157	.224	.210	-.250	-.646
	H(1:2)				.911	.251	-.240	-.270	-.543
	H(1:3)				-1.093	-.467	.079	.286	.396

The Classification output (Table VI) depicts the number of cases associated with each combination of actual and predicted values for the outcomes of certification upgrade. Predicted values lie upon the x-axis, with actual values depicted the y-axis. All sample sizes presented on the diagonals of the training and testing portions of the table correspond with cases in which the predicted and actual values on the outcome were identical. The further one deviates from this diagonal, the less accurate the predictions. In the training sample, 106 (208*0.51) cases were predicted perfectly out of a total of 208 cases, while in the testing sample, 30 (90*0.33) cases were predicted perfectly out of a total of 90 cases. Additionally, several predicted values have small deviations (1), which substantially increase these counts.

TABLE VI. *MLP CLASSIFICATION*

Classification

		Predicted					
Sample	Observed	1.00	2.00	3.00	4.00	5.00	Percent Correct
Training	1.00	50	12	0	1	0	79.4%
	2.00	18	29	1	0	6	53.7%
	3.00	4	19	0	0	7	0.0%
	4.00	3	10	0	0	15	0.0%
	5.00	2	4	0	0	27	81.8%
	Overall Percent	37.0%	35.6%	0.5%	0.5%	26.4%	51.0%
Testing	1.00	12	6	0	0	1	63.2%
	2.00	13	11	0	0	2	42.3%
	3.00	1	9	0	0	2	0.0%
	4.00	1	12	0	2	8	8.7%
	5.00	1	3	0	1	5	50.0%
	Overall Percent	31.1%	45.6%	0.0%	3.3%	20.0%	33.3%

Dependent Variable: Certification Advancement Intention

Fig. 2 plots the predicted pseudo-probabilities associated with each outcome. Actual outcomes are plotted on the x-axis. The predicted values of ‘1’ and ‘5’ are good exemplars of information depicted in Fig. 2. Moving from left to right on the graphic, the predicted pseudo-probabilities associated with the outcome of ‘1’ begin in the 0.55 range and decline to a value approaching zero. The reduction in predicted values indicates that the model is likely to predict a ‘1’. This occurs more than half the time when the actual outcome is equal to ‘1’ with the probability approaching zero when the actual outcome is equal to ‘5’. Similarly, among actual outcomes of ‘5’, the predicted pseudo-probability approaches zero when the actual outcome is ‘1’. Moving again from left to right, the values grow steadily to a position where the actual outcome is ‘5’. At this point the predicted pseudo-probability is approximately 0.35.

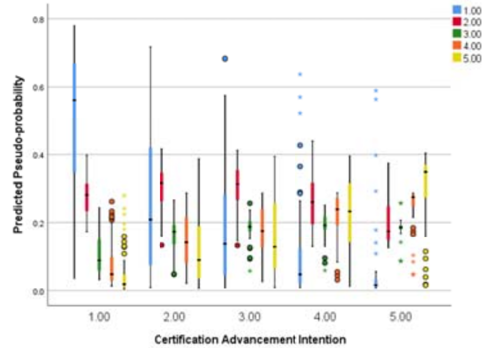

Fig. 2. MLP Predicted Pseudo-Probability

Fig. 3 illustrates sensitivities and specificities associated with this MLP network using a ROC (receiver operating characteristic) curve. A ROC curve graphically illustrates the performance of a classifier system where the discrimination threshold is varied [38,25]. Plotted lines exhibiting greater area under the curve are associated with increased probability that a classifier will rank a randomly chosen positive case higher than a randomly chosen negative case. This ranking presumes that 'positive' cases rank higher than 'negative' cases. Fig. 3 indicates that probability was highest for the actual outcomes of ‘1’ and ‘5’, with moderate an outcome for ‘4’, and lowest outcomes for ‘2’ and ‘3’. Interpreting these results in conjunction with the Classification output (Table VI), the values of ‘1’ have a percentage correctly predicted of 79.4% and 63.2% for the training and testing samples, respectively. Corresponding values for the outcome of ‘5’ were 81.8% and 50.0%, respectively. For outcome ‘2’, values were 53.7% and 42.3%. Outcome ‘3’ predicted 0.0% for both samples, with 0.0% and 8.7% for outcome ‘4’.

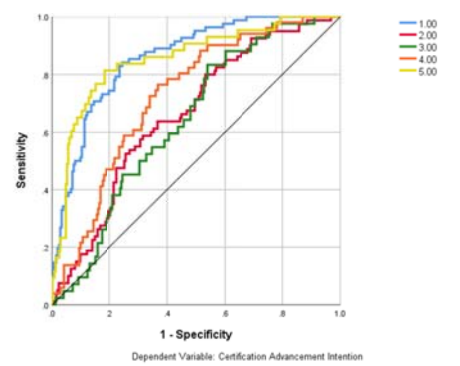

Fig. 3. MLP Receiver Operating Characteristic (ROC) Curve

The Area Under the Curve (Table VII) presents actual probabilities, which are associated with the calculated area under the curve.

TABLE VII. *MLP AREA UNDER THE CURVE*

Area Under the Curve

		Area
Certification Advancement Intention	1.00	.859
	2.00	.661
	3.00	.640
	4.00	.725
	5.00	.855

The Independent Variable Importance output (Table VIII) presents the importance and normalized importance associated with each of the IVs. Normalized importance measures consist simply of each importance measure, divided by the largest importance measure, and expressed as a percentage. The IV of greatest importance depicts a normalized importance of 100%. These results indicate that time commitment (TIME) had the greatest importance with respect to predicted outcomes, followed by responsibility (RESP), elapsed time (ELAPSED), educational support (EDUC), peer appraisal (PEER), and locus of control (LOC).

TABLE VIII. *MLP INDEPENDENT VARIABLE IMPORTANCE*

Independent Variable Importance

	Importance	Normalized Importance
Time Commitment	.331	100.0%
Elapsed Time	.182	54.9%
Peer Appraisal	.071	21.3%
Locus of Control	.041	12.4%
Responsibility	.300	90.8%
Educational Support	.075	22.8%

Normalized Importance (Fig. 4) simply plots importance and normalized importance measures in graphical format.

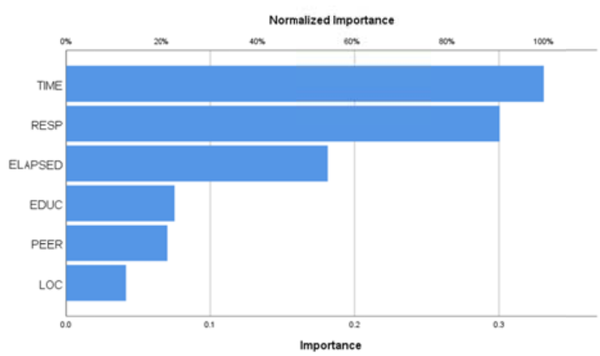

Figure 4. MLP Normalized Importance

IV. RBF NETWORK

The RBF Case Processing Summary output (Table IX) is akin to the MLP output, which depicts sample sizes and response percentages associated with training and testing samples. The specified 70/30 split between training and testing reflected 213 cases (71.5%) for the training sample and 85 cases (28.5%) for the testing sample. For reference, the MLP allocation was 208 cases (69.8%) for the training sample and 90 cases (30.2%) for the testing sample.

TABLE IX. *RBF CASE PROCESSING SUMMARY*

Case Processing Summary

		N	Percent
Sample	Training	213	71.5%
	Testing	85	28.5%
Valid		298	100.0%
Excluded		0	
Total		298	

The Network Information output (Table X) and Layer Activation graphic (Fig. 5) present a neural network diagram comparable to the MLP analysis supra. Two important differences are the existence of five artificial neurons in the hidden layer, and that RBF does not produce bias values.

TABLE X. *RBF NETWORK INFORMATION*

Network Information

Input Layer	Covariates	1	Time Commitment
		2	Elapsed Time
		3	Peer Appraisal
		4	Locus of Control
		5	Responsibility
		6	Educational Support
	Number of Units		6
	Rescaling Method for Covariates		Standardized
Hidden Layer	Number of Units		5[a]
	Activation Function		Softmax
Output Layer	Dependent Variables	1	Certification Advancement Intention
	Number of Units		5
	Activation Function		Identity
	Error Function		Sum of Squares

a. Determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

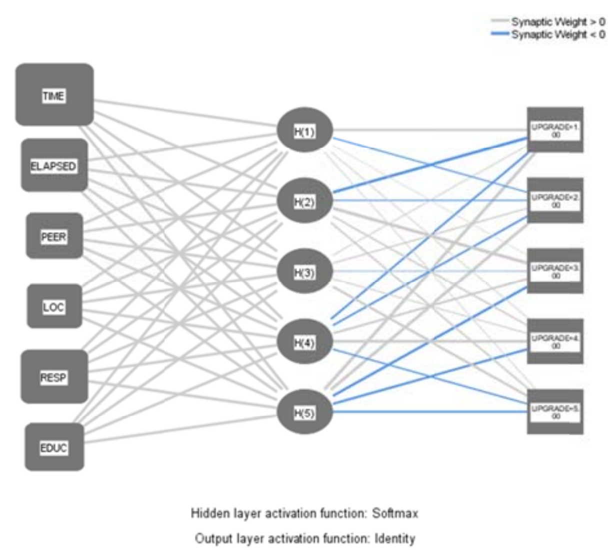

Figure 5. RBF Layer Activation

The Model Summary output (Table XI) presents statistics related to the performance of this neural network. In the training sample, 56.8% of predictions were characterized as incorrect predictions. The testing sample comprised a lesser proportion of incorrect predictions at 55.3%. The sum of squares error is 68.18 in the training sample and 27.51 in the testing sample.

TABLE XI. *RBF MODEL SUMMARY*

Model Summary

Training	Sum of Squares Error	68.176
	Percent Incorrect Predictions	56.8%
	Training Time	0:00:00.15
Testing	Sum of Squares Error	27.511[a]
	Percent Incorrect Predictions	55.3%

Dependent Variable: Certification Advancement Intention
a. The number of hidden units is determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

The Parameter Estimates output (Table XII) is interpreted in a similar manner to the MLP output except for the exclusion of bias values. Predicted values for certification upgrade outcomes, again, are calculated with reference to the *layer activation* graphic (Fig. 5).

TABLE XII. *RBF PARAMETER ESTIMATES*

Parameter Estimates

Predictor		Predicted: Hidden Layer[a] H(1)	H(2)	H(3)	H(4)	H(5)	Output Layer [UPGRADE=1.00]	[UPGRADE=2.00]	[UPGRADE=3.00]	[UPGRADE=4.00]	[UPGRADE=5.00]
Input Layer	TIME	-.791	.091	1.050	.469	-.049					
	ELAPSED	.629	-.052	-1.015	-.291	.060					
	PEER	-.429	-.208	.475	.346	.098					
	LOC	.336	-.309	-.268	.037	-.097					
	RESP	-.444	-.012	.494	.485	-.107					
	EDUC	-.526	.084	.532	.183	.136					
Hidden Unit Width		1.054	1.050	1.438	1.184	1.144					
Hidden Layer	H(1)						.998	-.120	.005	.060	.056
	H(2)						-1.240	-.083	1.899	.208	.215
	H(3)						.065	.194	-.054	.076	.719
	H(4)						-.318	-.288	.407	1.399	-.200
	H(5)						1.496	1.484	-.924	-.688	-.368

a. Displays the center vector for each hidden unit.

The Classification Table output (Table XIII), comparable fashion to the MLP output, depicts the number of cases associated with each combination of actual and predicted values for the outcomes of certification upgrade. In the training sample, 192 (213*0.432) cases were predicted perfectly out of a total of 192 cases. In the testing sample, 38 (85*0.447) cases were predicted perfectly out of a total of 85 cases. Several predicted values have small deviations (1) that substantially increase these counts.

TABLE XIII. *RBF CLASSIFICATION*

Classification

Sample	Observed	Predicted 1.00	2.00	3.00	4.00	5.00	Percent Correct
Training	1.00	45	11	2	3	0	73.8%
	2.00	19	15	4	9	7	27.8%
	3.00	6	10	4	9	1	13.3%
	4.00	5	8	3	14	9	35.9%
	5.00	1	4	2	8	14	48.3%
	Overall Percent	35.7%	22.5%	7.0%	20.2%	14.6%	43.2%
Testing	1.00	17	2	0	0	2	81.0%
	2.00	10	8	1	4	3	30.8%
	3.00	0	9	2	0	1	16.7%
	4.00	0	4	3	2	3	16.7%
	5.00	1	1	0	3	9	64.3%
	Overall Percent	32.9%	28.2%	7.1%	10.6%	21.2%	44.7%

Dependent Variable: Certification Advancement Intention

Fig. 6 plots the predicted pseudo-probabilities associated with each outcome in a comparable manner to the MLP analysis supra. Actual outcomes are plotted on the x-axis. The predicted values of '1' and '5' are good exemplars of information depicted in Fig. 6. Moving from left to right on the graphic, the predicted pseudo-probabilities associated with the outcome of '1' begin in the 0.62 range and decline to a value approaching zero. The reduction in predicted values indicates that the model is likely to predict a '1'. This occurs over 50 percent of the time when the actual outcome is equal to '1' with the probability approaching zero when the actual outcome is equal to '5'. Among actual outcomes of '5', the predicted pseudo-probability approaches zero when the actual outcome is '1'. Moving from left to right the values grow steadily to a position where the actual outcome is '5'. At this point the predicted pseudo-probability is 0.4.

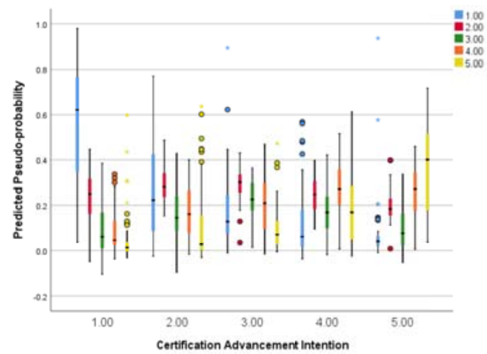

Figure 6. RBF Predicted Pseudo-Probability

Fig. 7 illustrates sensitivities and specificities associated with this MLP network using a ROC curve. The information in Fig. 7 indicates that probability was highest for the actual outcomes of '1' and '5', with moderate outcomes for '3' and '4', and the lowest outcome for '2'. Interpreting these results in conjunction with the Classification Table (Table XIII), the values of '1' have a percentage correctly predicted of 73.8% and 81.0% for the training and testing samples, respectively. Corresponding values for the outcome of '5' were 48.3% and 64.3%, respectively. Regarding outcome '2', values were 27.8% and 30.8%. Outcome '3' predicted 13.3% and 16.7, with 35.9% and 16.7% for outcome of '4'.

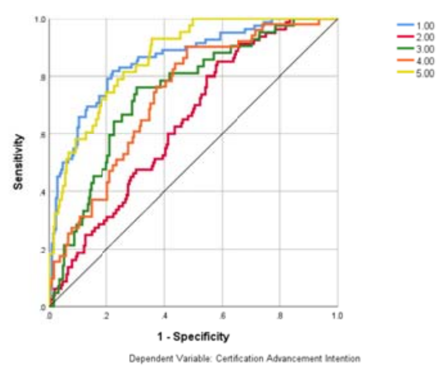

Figure 7. RBF Receiver Operating Characteristic (ROC) Curve

The Area Under the Curve (Table XIV) presents actual probabilities associated with the calculated areas under the curve.

TABLE XIV. *RBF AREA UNDER THE CURVE*

Area Under the Curve

		Area
Certification Advancement Intention	1.00	.856
	2.00	.641
	3.00	.743
	4.00	.733
	5.00	.866

The Independent Variable Importance (Table XV), which is akin to the MLR output, presents the importance and normalized importance associated with each of the IVs. The IV of greatest importance depicts a normalized importance of 100%. These results indicate that time commitment (TIME) had the greatest importance with respect to predicted outcomes, followed by responsibility (RESP), elapsed time (ELAPSED), educational support (EDUC), peer appraisal (PEER), and locus of control (LOC). The ranked order of importance for the six IVs is the same for both MLP and RBB methods.

TABLE XV. *RBF INDEPENDENT VARIABLE IMPORTANCE*

Independent Variable Importance

	Importance	Normalized Importance
Time Commitment	.248	100.0%
Elapsed Time	.183	73.9%
Peer Appraisal	.127	51.3%
Locus of Control	.117	47.2%
Responsibility	.186	74.9%
Educational Support	.139	56.3%

Normalized Importance (Fig. 8) simply plots importance and normalized importance measures in graphical form to reflect the numerical rankings in the Independent Variable Importance graphic (Table XV).

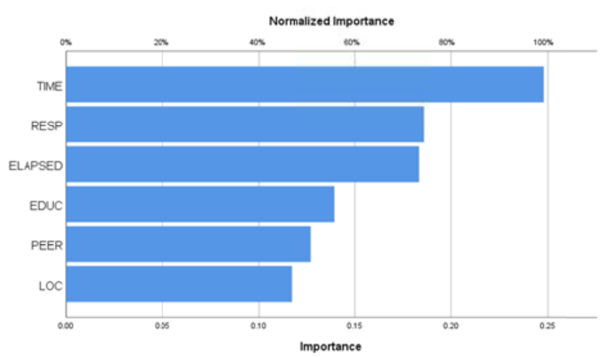

Figure 8. RBF Normalized Importance

TABLE XVI. *MLR, MLP AND RBF COMPARISON*

Variable	MLR (r^2)	OLR (Exp_B)	OLR Wald $\chi^2(1)$	MLP (Importance)	RBF (Importance)
Time Commitment (TIME)	0.49**	4.524**	64.357**	0.331	0.248
Responsibility (RESP)	0.27**	2.471**	11.554**	0.300	0.186
Elapsed Time (ELAPSED)	0.25**	0.343**	25.178**	0.182	0.183
Educational Support (EDUC)	0.17**	0.851	0.473	0.075	0.139
Peer Appraisal (PEER)	0.12**	1.374	1.503	0.071	0.127
Locus of Control (LOC)	0.03	0.732	2.675	0.041	0.117

Table XVI depicts comparative results for MLR, OLR, MLP, and RBF analyses. The overall priority ranking of the IVs is time commitment (TIME), responsibility (RESP), elapsed time (ELAPSED), educational support (EDUC), peer appraisal (PEER), and locus of control (LOC) with the exception of the Wald $\chi2(1)$ value, which ranks elapsed time (ELAPSED) ahead of responsibility (RESP). The results of ANN analysis may be considered consistent with the MLR and OLR results generated in the 2018 dissertation.

V. LIMITATIONS

Research limitations existing in the 2018 dissertation research attach to this study. Potential limitations related to the validity and reliability of the pilot study generated from the original survey. Employing 'combined' measures with OLR, rather than 'individual' measures, reduced the overall number of tests required in the analysis. Fewer tests assisted to manage Type 1 error. However, when combining measures into a single measure for the purposes of analysis, reliability needs to be sufficiently high [43]. Study results were limited by the number of respondents available to participate in the survey. Wildfires in the Fort McMurray region [44], and the lower commodity price for oil [45,46] adversely affected the facilities and the sample responses. Convenience sampling was a further study limitation as results generated may only be applied to the sample analyzed. To the extent that the characteristics of the convenience sample resembled or could be used to represent certified power engineers in other provinces, the results of the study are important to the interprovincial-certified power engineering community. The generalization of results from the population from which the sample was derived, or any other population, would need to be tentative at best. The sample was limited to two Canadian provinces with the results being less generalizable to other geographical areas. This paper provides a foundational quantitative platform for further power engineering research.

VI. DISCUSSION

The objective of this paper was to compare standard regression results generated from a 2018 dissertation power engineering dataset with complementary ANN analysis of the same dataset. Regression analysis is a parametric method for investigating relationships between several IVs and a DV. Specification of the analytical expression of the functional form connecting both inputs and outputs is necessary under regression methodology. Conversely, neural networking is a non-parametric method without requirement for analytical expressions linking inputs and outputs [34]. Comparative analysis between standard regression and ANN regression permitted determination of the relative ranking of decision factors that influence advancement intention. The purpose of the complementary ANN analysis was to further investigate factors influencing Canadian power engineers' decision or intention to pursue advanced certification in a comparative manner. Performing complementary analysis provided additional perspective and insight, but also introduced uncertainty regarding analytical processes and selection of methods. Specifically, ANN was chosen as a follow-up analysis to MLR and OLR. Eromietse and Joseph (2019) [31] noted that ANN may perform better or worse than standard regression applications, such as logit models, for predictive functions. The level of predictive performance and accuracy is related to aspects such as researcher experience and knowledge, as well as network configuration. The key goal of the power engineering study was to identify factors influencing decision-making through statistical analysis. Mathematical modeling techniques for enhancing decision-making is pervasive in business, economics, and research, which as integral to the energy sector. A neural network model was an obvious choice to complement standard regression analyses using the same power engineering dataset.

VII. Recommendations for Future Research

Research into factors influencing advancement intention in Canadian power engineering explores decision processes and the construct of 'intention'. Indicated in the abstract was the requirement for both quantitative and qualitative perspectives when endeavoring to understand behaviour. The qualitative humanistic element in this paper represented structural (external to the individual) and humanistic (internal to the individual) IV influences on the DV of advancement intention. The structural influences were presented through the variables of time (committed and elapsed) and educational support. The humanistic influences presented as responsibility, locus of control orientation, and peer appraisal. The quantitative portion of the paper involved the analysis of survey question responses operationalized as numerical surrogates. ANNs represent endeavours to replicate organic brain architecture and processes through digital means. Parallels may be drawn between organic neural behavioural drivers and mathematical models for describing or predicting behaviour.

Decision-making embraces the praxeological perspective comprising interplay between cognitive (brain-based) reasoning and digital (algorithm-based) applications. Garibaldo and Rebecchi (2018) [47] cited praxeology in this context as, "a perspective for analyzing the complex interplay of algorithmically determined physical data processing with the social process of signifying or interpreting the data in the context of an organization's social practices" (p. 301). Decision processes within the framework of the power engineering study involved factors influencing the intention of the power engineer. Futerman and Block (2017) [48] emphasized the relationship between 'intentional action' and praxeology through Ludwig von Mises's 'action axiom'. This axiom contends that all humans strive to exchange a less desirable situation, for one that is more desirable. This aspiration appears obvious and straightforward until the process and effort required to change conditions is contemplated. The power engineer introspectively calculates the requirements for advancement, and determines the effort required for advancement. This calculus includes those structural and humanistic elements investigated through the analytical mediums of MLR, OLR, and ANN.

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