The use of artificial neural networks (ANN) in the prediction of energy consumption of air-source heat pump in retrofit residential housing

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Abstract. Machine learning algorithms using Artificial Neural Network (ANN) were developed to predict the performance of heat pump systems in retrofit residential housing. The study attempts to address the research gap in the application of machine learning algorithms to real-life field measurements as a case study. Rowhouse units with electric resistance baseboard heating were retrofitted with Ductless Air Source Heat Pumps (DASHPs). Sensors were installed to collect the energy consumption data during the baseboard and DASHP monitoring periods. Linear and quadratic regression methods following the International Performance Measurement and Verification Protocol (IPMVP) were applied to predict energy consumption based on outdoor temperature and heating degree days. These predictions were compared against results from ANN models based on Levenberg-Marquardt algorithms using the hour of the day, day of the week, outdoor temperature, wind speed and direction, relative humidity, condition and indoor temperature as inputs. Preliminary results indicate that predictions from ANN models produced higher correlation of determination than those from IPMVP regression analysis.

Keywords: Artificial Neural Network, Air-Source Heat Pump, Measurement & Verification

1. Introduction
Heat pump retrofits are a significant conservation opportunity in the residential sector because they can supplement the electrical energy used for space heating with heat energy extracted from the air or ground to drastically reduce energy consumption for space heating. While heat pump retrofits have great potential to reduce the residential sector’s energy demands, the lack of appropriate measurement & verification (M&V) procedures is a significant barrier to their widespread adoption. An effective M&V procedure which minimizes the uncertainty in cost savings would encourage property owners and local distribution companies to implement retrofits [1]. This study evaluated the energy savings from ductless multi-split air-source heat pump retrofits in a rowhouse complex located in Brantford, Ontario, Canada, using multiple methods and compared the results of each approach.
2. Methodology
Six 2- or 3-bedroom rowhouse units participated in the study. Four rowhouse units received ductless multi-split heat pump retrofits donated by two different manufacturers. Details of the M&V process for all six rowhouse units for both the heating and cooling seasons can be found in the full report by the Toronto and Region Conservation Authority’s Sustainable Technologies Evaluation Program (STEP) [2]. This paper focuses on the analysis of Rowhouse Unit 3 and Unit 4 during the 2017/2018 heating season. Both rowhouse units are situated in the middle of the rowhouse complex shown in Figure 1 (a). Table 1 summarizes the heat pump retrofits on each unit and their corresponding monitoring periods.

| Unit | Bedrooms | Heat Pump Type | Baseline Monitoring Period (Electric Baseboard) | Retrofit Monitoring Period (DASHP) |
|------|----------|----------------|-----------------------------------------------|-----------------------------------|
| 3    | 2        | 3-Port Cold-Climate (HSPF 12.5) | 01/20/2018 to 03/01/2018 | 11/20/2017 to 01/18/2018 |
| 4    | 3        | 4-Port Conventional (HSPF 11.0) | 01/20/2018 to 03/01/2018 | 11/20/2017 to 01/18/2018 |

2.1. Heat pump installation and instrumentation
The heat pumps were sized to meet the demands of the house with one indoor fan coil on the first floor’s main living space and one in each bedroom. A remote monitoring system was installed in the six study rowhouse units to measure house’s conditions and energy demands and then derive energy savings associated with the heat pumps. The monitoring system includes energy submeters for the heat pumps, sensors which measured the indoor and outdoor air temperatures and relative humidity in the main living space, and a dedicated submeter to measure the total energy consumption in each rowhouse unit.

During the retrofit monitoring period, heat pumps were used to provide heating to Units 3 and 4. The baseline heating data was obtained by turning off the heat pumps in these units for several weeks and providing heating exclusively through the pre-existing electric baseboard heaters.

2.2. International Performance Measurement and Verification Protocol (IPMVP) Option C
The IPMVP, developed by the Efficiency Evaluation Organization in the 1990s, is a standardized method for evaluating energy savings. The method determines savings using energy measurements taken during both a Baseline Period (before the retrofit) and a Reporting Period (after the retrofit) with adjustments. These measurements were normalized against weather effects and evaluated for savings.

Several issues were brought to attention through tenant interviews and prompted adjustments to the dataset. These includes cases such as intentionally increasing heating for one space during certain weeks, accidentally leaving baseboard heaters on, and irregular usage patterns during holidays. The exclusion and filtering of data in these cases account for the adjustments.

Linear and polynomial regression was used to model the energy consumption during the baseline and retrofit periods respectively. First, the balance point temperature, $T_b$, the outdoor temperature above which the energy consumption of the heat pump becomes 0 kWh, was found to be 16°C for Unit 3 and 11°C for Unit 4 through regression analysis. This study uses the heating degree day (HDD) as the independent variable and correlates it to the sub-metered energy consumption of the rowhouse unit. The data was aggregated into daily values from the 10-minute interval data. The HDD values are using Equation 4, where $T_o$ is the daily average outdoor temperature.

$$HDD_k = T_b - T_o$$

The baseline total $B(HDD_k)$, retrofit total $R(HDD_k)$, and heat pump $H(HDD_k)$ energy consumptions are then obtained as functions of HDD from the regressions. These functions were then applied to the Canadian Weather Year for Energy Calculation (CWEC) 2016, a statistically averaged weather dataset.
developed by Environment Canada. The CWEC 2016 Hamilton International Airport weather data was used as an approximation for Brantford. The normalized total energy consumption of the baseline monitoring period is calculated by taking the sum of discrete bins of HDD values (in 1°C-d/Day increments) with an upper bound $HDD_{max}$ corresponding to the outdoor temperature which causes the heat pumps to shut off for freeze protection. The total normalized energy consumption during the baseline period $B_{tot}$ is calculated using Equation 2. The normalized total energy consumption for the retrofit period $R_{tot}$, and the heat pump energy consumption $H_{tot}$ are calculated the same way. The $HDD_{max}$ is at 34°C-d/day for Unit 3 and 26°C-d/day for Unit 4. $n_k$ is the number of days, which share the same HDD increment.

$$B_{tot} = \sum_{k=0}^{HDD_{max}} B(HDD_k) \cdot n_k$$ (2)

The total normalized energy savings for Unit 3 and Unit 4 are then found as the differences between the retrofit total energy consumption and their corresponding baseline total energy consumption (Equation 3). The normalized savings can then be used to calculate the coefficient of performance of the heat pumps over a typical heating season (Equation 4).

$$S_{tot} = B_{tot} - R_{tot}$$ (3)
$$COP = \frac{S_{tot} + H_{tot}}{H_{tot}}$$ (4)

2.3. Artificial neural networks

Artificial Neural Networks (ANN) have been extensively used in several disciplines in solving complex problems which require optimization, manufacturing, power systems, forecasting. ANNs offer an alternative methodology to deal with otherwise analytically complicated and ambiguous problems. ANNs can perform the complex task of prediction and generalization while being trained. They can learn from examples and are also fault tolerant in the sense that they can appropriately handle incomplete and noisy data [3]. ANNs are initially established to imitate the human brain. The architecture of ANN model consists of the network architecture, the number of hidden layers and number of hidden neurons [4]. Neurons are adjacent elementary altering units which create the neuronal model.

In this paper, ANN algorithms from Levenberg-Marquardt [5] are implemented. These models were first trained using the collected dataset from the baseline and retrofit monitoring periods. The data are separated randomly as 80% training, 15% validation, and 5% testing datasets by using 40 hidden neurons. The hour of the day, day of the week, outdoor temperature, wind speed and direction, relative humidity, condition and indoor temperature are included in addition to HDD for a total of 9 input variables. The target output is the predicted energy consumption of either the heat pump or the whole rowhouse unit. After the models have been generalized, they were applied to the CWEC 2016 weather data to predict the annual heating season energy consumption of each rowhouse unit before and after the retrofit. The predicted results were used to determine the total energy savings throughout the year using Equation 3.

3. Results

The regression models developed for Unit 3 using IPMVP Option C is shown in Tables 2 and 3. The reported uncertainty of the predicted value was determined using the t-distribution for the 95% confidence interval following the IPMVP Statistics and Uncertainty Section 2.2.2 [6]. Unit 3 shows acceptable fits with coefficient of correlation ($R^2$) higher than 0.8. Unit 4 shows a significantly lower $R^2$ due to the widely varying occupant energy usage patterns aside from the heating loads. The annual heating season energy consumption predictions of the regression are summarized and compared against the ANN models’ predictions in Table 6.
Table 2. Unit 3 Regression Models

| Description                          | Energy Consumption Equation (kWh/day) | $R^2$ | Standard Error (kWh/day) |
|--------------------------------------|--------------------------------------|-------|--------------------------|
| Baseline monitoring period total     | $B(HDD_k) = 1.9684 \cdot HDD_k + 17.02$ | 0.89  | 3.90                     |
| Retrofit monitoring period total     | $R(HDD_k) = 0.0347 \cdot HDD_k^2 + 0.3966 \cdot HDD_k + 16.09$ | 0.80  | 4.79                     |
| Retrofit monitoring period heat pump | $H(HDD_k) = 0.0037 \cdot HDD_k^2 + 0.9408 \cdot HDD_k + 1.4182$ | 0.88  | 2.47                     |

Table 3. Unit 4 Regression Models

| Description                          | Energy Consumption Equation (kWh/day) | $R^2$ | Standard Error (kWh/day) |
|--------------------------------------|--------------------------------------|-------|--------------------------|
| Baseline monitoring period total     | $B(HDD_k) = 2.1256 \cdot HDD_k + 46.95$ | 0.44  | 12.86                    |
| Retrofit monitoring period total     | $R(HDD_k) = -0.0428 \cdot HDD_k^2 + 2.5925 \cdot HDD_k + 29.27$ | 0.36  | 10.94                    |
| Retrofit monitoring period heat pump | $H(HDD_k) = 0.0297 \cdot HDD_k^2 + 1.4639 \cdot HDD_k + 3.46$ | 0.85  | 4.29                     |

A method prevalent throughout literature to evaluate the efficiency of the ANN algorithms implemented is based on the criteria of $R^2$ the mean square error (MSE) [7]. Similarly, this study evaluates these metrics for the data analysis of each rowhouse unit as summarized in Tables 4 and 5.

Figure 2. Plots of the fit between the ANN model’s predicted Rowhouse Unit 3 heat pump energy consumption values (Y) and the actual consumption or target values (T) after training the network.
Table 4. Unit 3 ANN Algorithm Test Results

| Description                      | Number of Datapoints | R²   | Mean Squared Error | Standard Error (kWh/hour) | Standard Error (kWh/day) |
|----------------------------------|----------------------|------|--------------------|---------------------------|--------------------------|
| Baseline monitoring period total | 945                  | 0.550| 0.186              | 0.433                     | 2.120                    |
| Retrofit monitoring period total | 2619                 | 0.400| 0.236              | 0.487                     | 2.390                    |
| Retrofit monitoring period heat pump | 2619            | 0.820| 0.021              | 0.146                     | 0.710                    |

Table 5. Unit 4 ANN Algorithm Test Results

| Description                      | Number of Datapoints | R²   | Mean Squared Error | Standard Error (kWh/hour) | Standard Error (kWh/day) |
|----------------------------------|----------------------|------|--------------------|---------------------------|--------------------------|
| Baseline monitoring period total | 926                  | 0.460| 1.005              | 1.008                     | 4.940                    |
| Retrofit monitoring period total | 2154                 | 0.250| 1.577              | 1.259                     | 6.170                    |
| Retrofit monitoring period heat pump | 2154            | 0.830| 0.045              | 0.213                     | 1.040                    |

The results show that the correlation between the predicted hourly heat pump energy consumption and the inputs is high, while the correlation between the predicted hourly rowhouse total energy consumption and the inputs is much weaker. When comparing the ANN test results to the regression method, although the correlation coefficients from the ANN models may only seem marginally higher for Unit 4 and lower for Unit 3, it is important to note that the ANN models are making hourly as opposed to daily predictions. As shown in Figure 3, the regression method shows a high degree of scatter if analysed on an hourly basis, especially in rowhouse Unit 4 with a significantly low correlation of \( R^2 = 0.04 \). The ANN model in comparison shows a much better fit for the hourly data.

Figure 3. Regressions with low \( R^2 \) on hourly total energy consumption in Rowhouse Units 3 and 4 during the retrofit monitoring period.

Table 6. Comparison of Predicted Heating Season Energy Consumption and Savings

| Predicted Value | Description                              | Unit 3 Regression (kWh/year) | Unit 3 ANN (kWh/year) | Unit 4 Regression (kWh/year) | Unit 4 ANN (kWh/year) |
|-----------------|------------------------------------------|------------------------------|-----------------------|-----------------------------|-----------------------|
| \( B_{tot} \)   | Baseline heating season total energy consumption | 10776 ± 126               | 10566 ± 67             | 13925 ± 368                 | 13254 ± 140           |
| \( R_{tot} \)   | Retrofit heating season total energy consumption | 7376 ± 154                | 6402 ± 76              | 10060 ± 313                | 10742 ± 175           |
| \( H_{tot} \)   | Retrofit heating season heat pump energy consumption | 3648 ± 80                 | 3245 ± 23              | 4685 ± 123                 | 4819 ± 30             |
| \( S_{tot} \)   | Heating season energy Savings            | 3400 ± 199                | 4164 ± 79              | 3865 ± 484                 | 2512 ± 177            |
Table 7. Comparison of Predicted Heat Pump Heating Seasonal COP

|          | Rowhouse | Regression | ANN |
|----------|----------|------------|-----|
| Unit 3   | 1.93     | 2.28       |     |
| Unit 4   | 1.83     | 1.52       |     |

4. Discussion and Conclusion

The use of ANN in predicting the energy consumption patterns of buildings have both advantages and limitations when compared to weather normalization and regression. ANN models provide results with greater $R^2$ and smaller Standard Errors which translates into a reduction of 44-75% in uncertainty for the predicted values compared to regression. However, training ANN requires large datasets. Throughout the entire heating season in this study, less than 3000 useful hourly data points were collected on for each monitoring period and contributed to the low $R^2$ of the hourly ANN predictions. This showcases the challenge of collecting large quantities of useful data in real-life M&V scenarios. Regression is often a simpler method which predicts results with an acceptable level of uncertainty in scenarios when the energy usage patterns are regular, such as the case of Unit 3. Applying ANN to the M&V process may be beneficial when the occupant’s energy usage patterns for miscellaneous loads such as household appliances are highly irregular, such as in the case of Unit 4, and reduce a large amount of uncertainty when compared to predictions through regression. Both methods predicted similar levels of energy consumptions. The heat pump COP calculated from the savings estimates are also within reasonable agreement of ±0.35 for each heat pump type. The estimated COP for the entire heating season shows that there is significant heating energy savings potential for heat pump retrofits replacing electric baseboard heating.

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