Predicting and quantifying the effect of variations in long-term water demand on micro-hydropower energy recovery in water supply networks

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ABSTRACT
To improve water supply energy efficiency micro-hydropower turbines can be installed within networks at locations of excess pressure. However, future changes in flow rates and pressures at these locations could render an installed turbine unsuitable. It is therefore important that long term changes in flow conditions at potential turbine locations be considered at initial feasibility/design stages.
Using historical data over a ten-year period, this paper predicts the effects of changes in water flow rates at potential turbine locations in Ireland and the UK. Results show that future flow rates at these locations could be predicted with an $R^2$ of up to 66% using multivariate linear regression and up to 93% using artificial neural networks. Flow rates were shown to vary with population, economic activity and climate factors. Changes in flow rate were shown to have a significant impact on power output within the design life of a typical hydropower turbine.

1. Introduction

The supply and treatment of water is highly energy intensive, resulting in large amounts of greenhouse gas emissions as well as increased electricity consumption (McNabola et al. 2014, Sitzenfrei and von Leon 2014, Gallagher et al. 2015). In addition, climate change, as well as putting water sources under stress and influencing water usage patterns, has also lead to the enforcement of carbon emission reduction targets in the water industry (Howe 2009). Alternative options available to water service providers (WSPs) to achieve improvements include the installation of hydropower turbines.

The control of pressure to prevent burst pipes and reduce water leakage is also of great importance both operationally and economically for WSPs. The use of pressure reducing valves (PRVs) is commonplace for pressure management and leakage reduction. In recent years, the incorporation of micro-hydropower (MHP) turbines within water supply networks for electricity generation has been shown as a viable option for water pressure reduction as well as improving water supply carbon footprint (Ramos et al. 2010, Gonçalves et al. 2011, Carravetta et al. 2012, 2013, 2014, Fecarotta et al. 2015).

Changes in water demand impacts power output capacity at turbines within water distribution networks (WDNs). This has been reported as a barrier to the implementation of MHP in water networks due to its impact on financial viability in future (Colombo and Kleiner 2011, Corcoran et al. 2013, McNabola et al. 2013, Giugni et al. 2014, Sitzenfrei and von Leon 2014, Sitzenfrei and Rauch 2015). Flow rates in water supply networks vary considerably both diurnally and seasonally. Water demand can also change dramatically over longer periods, with changes in population, climate and economic activity. Long-term changes in water demand impact flow conditions at turbines. These changes could see large increases/decreases in flow rates, rendering turbine operating efficiencies decreased or turbines unsuitable.

The feasibility of small-scale hydropower within the WDN was recently investigated from a probabilistic perspective in order to address this issue of demand variation (Colombo and Kleiner 2011). Potential uncertainties were highlighted, including long-term demand growth, diurnal and seasonal demand variations, and future cost fluctuations. Similarly, Sitzenfrei and Rauch (2015) reported that neglecting the effects of long term demand uncertainty in small hydropower systems in WDNs results in unrealistic assessment of the economic viability of hydropower in this setting.

Small scale MHP sites often achieve investment payback after long periods e.g. 10 years (Corcoran et al. 2013). Over a 10 year period, it is important to consider how flow conditions through installed turbines may change. Sitzenfrei and von Leon (2014) simulated the operation of MHP systems in water networks over 10 years and optimized the turbines for maximum energy recovery. Changes in flow rate will affect turbine operation, efficiency, power production and return on investment. Therefore a methodology is required to enable water demand forecasting over the long-term at sites of interest for MHP within WDNs.

The majority of the literature on water demand forecasting is focused either on aggregate municipal demand or residential...
demand (Arbues et al. 2003). Forecasting for total municipal demand is required to ensure reservoirs are adequately supplied to meet future demands and for strategic infrastructure investment planning. Another stream of research is focused on residential water demand forecasting based on end-use analysis (Khatri and Vairavamoorthy 2009, Barua et al. 2016). Investigators have used methodologies such as multiple linear regression analysis (Barua et al. 2016), artificial neural networks (Donkor et al. 2014) and the fuzzy logic approach (Altunkaynak et al. 2005, Vijayalaksmi and Jinesh Babu 2015) to make these forecasts at household, district metered area or whole network level. This paper presents a different and novel approach to demand forecasting, focusing on flow rate fluctuation at valves within the WDN. This proposed new method considers influential factors, local to the installation point of a potential turbine, which may influence long term flow rates variations. Such water demand forecasting capabilities at specific points within a network may also have applications outside that of micro-hydropower energy recovery.

This paper also assesses the impact of long-term changes in flow rate at potential MHP energy recovery sites within WDNs, using specific case studies in Ireland and the UK. The impact of predicted long term changes in flow at potential MHP sites is quantified in terms of power generation.

2. Methodology

2.1. Experiment design

Multiple linear regression (MLR) was initially employed to establish the key influential variables affecting water flow rate variation at 16 existing water network valve sites in the UK and Ireland. These valves included PRVs and control valves potentially suitable for replacement with MHP turbines. The exploratory analysis allowed for the selection of variables to be included in further regression models, as well as the selection of a time step size. Following an initial hourly regression analysis, MLR was again employed on the ten years of data, at a quarterly time step, to enable the investigation of longer term socio-economic trends on water flow rate variation. Artificial neural networks (ANNs) were then employed to develop a model for predicting water flow rates at these valves using the same input data as for the MLR analysis. Finally, a scenario-based analysis was employed using the two prediction models developed to predict long term flow rates at these valves. Two scenarios were analysed to predict the flow rate at these valves in 2020 and 2030. For all models, both MLR and ANN were applied within the MATLAB environment.

The use of ANNs for forecasting has been primarily adopted for short-medium term forecasting timeframes in previous investigations. MLR has been adopted for both short-term and long-term forecasts. Short-term water demand forecasts can be accurately forecast with some models reporting $R^2 > 0.9$. Longer term forecasting models however are considered moderately accurate with $R^2$ values of above 0.3–0.4 (House-Peters and Chang 2011, McDonald et al. 2011).

2.2. Data overview

A long-term flow variation analysis was undertaken on a dataset covering a ten-year period from 2002 to 2012. A ten-year analysis timeframe was chosen because for a water supply MHP project to be deemed economically feasible, investment payback is generally required to be achieved within ten years (Corcoran et al. 2013). If flow rates could be predicted accurately for this ten-year period, a more suitable turbine could be selected to maximise power generation and ensure the investment is paid back within this period (Sitzenfrei and von Leon 2014).

Eleven valves within the water network of Dublin city (Ireland) and five valves in Wales (United Kingdom) were investigated. The locations of these valves are indicated in Figure 1. Telemetry data of flow and pressure were analysed from recordings at a resolution of 15 minutes. The flow and pressure data in Dublin included 8 PRVs and one reservoir (containing two control valves). All Welsh valves were PRVs. Table 1 provides an overview of the data analysed for each valve including an approximate estimate of the energy generation potential at each valve based on average flow rate and pressure drop in 2012, and assuming a conservative constant turbine-system efficiency of 65%.

The variation in average annual flow rate for some of the Dublin city valves is illustrated in Figure 2 (and for all valves in Figure S2 in the supplementary materials section), showing that the average flow rates for each valve varied year on year from 2002–2012 by as much as 350% in some cases.

The most frequently reported influencing factors on water demand can generally be classified as either climatic or socio-economic. Climate factors such as temperature, rainfall and relative humidity have been shown to affect water usage. McDonald et al. (2011) reported the key determinant of water demand in a region to be population. House-Peters and Chang (2011) reported the most common explanatory variables to be: temperature, precipitation, wind speed, evapotranspiration, water price, income and household size, amongst others. The consensus in the field is that short to medium term water demand forecasting is usually dependent on weather variables, whereas longer term water demand variance is more likely to be determined by socio-economic factors (Donkor et al. 2014).

Socio-economic data were obtained from the Central Statistical Office (CSO) in Ireland and the Office of National Statistics (ONS) in the UK. Other socio-economic variables obtained for inclusion in this analysis were the volume of production indices for the construction industry and the number of houses built. These were identified as indicators of economic growth, potentially influencing water usage. Climate data for the ten-year period was also obtained, including hourly data from weather stations in Dublin and in Wales. Water leakage rates from Welsh Water mains were sourced from the Welsh Water Annual Report (Welsh Water Dwr Cymru 2003–2013). The equivalent water leakage data for Dublin City Council (DCC) mains were sourced from DCC.

The effect of water charges on the water flow rates in Wales was also included (OFWAT 2014). Ireland did not charge directly for domestic water usage during the study period.

2.3. Hourly data investigation

Initial linear regression models were developed using hourly flow and climatic data. The primary purpose of this initial data exploration was to enable the selection of appropriate variables and time-steps to employ for the later development of longer term predictive models.
As well as the climatic variables, other variables relating to the
time of the day, the day of the week, weekday versus weekend
and the month were also investigated. These are all variables that
are commonly included in short-term water demand prediction
models.

A further investigation of diurnal variation in flow rates was
then undertaken at each valve. Trends in diurnal variation based
on the hour of the day and the day of the week were investigated.
Average annual demand patterns were calculated and plotted.
The annual changes in these diurnal flow rate patterns were
analyzed to investigate how these daily water usage patterns
varied over the ten year period.

2.4. Multiple linear regression (MLR)
MLR was again employed on the ten years of data, this time at a
quarterly time-step. Quarterly time-steps were selected because
the majority of the socio-economic data available was produced
on a quarterly basis. This longer duration of time-step for anal-
ysis enabled the investigation of relationships between water

Figure 1. Location of 16 water supply network, pressure reducing valves in Ireland and Wales. An enlarged image of the Dublin city valves is provided in the supplementary
materials section.

Table 1. Overview of data for analysis.

| Valve ID | Name              | 2012 Power Output (MWh) | Valve ID | Name              | 2012 Power Output (MWh) |
|---------|-------------------|-------------------------|---------|-------------------|-------------------------|
| Irish Valves |                 |                         | Welsh Valves |                 |                         |
| V1      | Blackhorse Bridge | 692.39                  | V12     | Llanishem West    | 81.47                   |
| V2      | Brunswick St.     | 143.66                  | V13     | Mountpleasant     | 90.23                   |
| V3      | Cookstown Res. 1  | NA                      | V14     | Pontypool         | 134.03                  |
| V4      | Cookstown Res. 2  | NA                      | V15     | Rhdyfelin         | 42.92                   |
| V5      | Donnybrook        | 244.05                  | V16     | Risca             | 275.06                  |
| V6      | Merrion           | 195.26                  |         |                   |                         |
| V7      | Poplar Row        | 151.90                  |         |                   |                         |
| V8      | Rainsford St.     | 216.37                  |         |                   |                         |
| V9      | Rialto Bridge     | 441.07                  |         |                   |                         |
| V10     | Slievebloom       | 246.07                  |         |                   |                         |
| V11     | Thomas Court      | 754.50                  |         |                   |                         |
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locations within WDNs as opposed to forecasting water demand for an entire catchment area (Goodchild 2003, Bougadis and Adamowski 2005, Babel and Shinde 2011, Haque et al. 2013). Long-term forecasts for specific locations within WDNs have not been reported upon in literature. Secondly, ANNs and their performance for short-term water demand forecasts have been reported upon in literature (Jain et al. 2001, Jain and Ormsbee 2002, Babel and Shinde 2011, Adamowski et al. 2012) however, long-term forecasts as developed in this research have not been widely researched.

ANNs can be applied to generalise non-linear relationships between input and output data. The primary influential variables listed in Table 2 were again used as the inputs for the development of ANN algorithms. The output data was the average flow rate at each valve in each quarter. A direct comparison could then be made between the accuracy of these two prediction methods.

Hybrid methodologies, such as the use of both MLR to select the optimal input variables, followed by ANN modelling has been reported on by Babel and Shinde (2011) and Donkor et al. (2014). Hybrid composite forecasts have been reported as being more effective than either ANNs or MLR on their own for short-term water demand forecasting (Adamowski et al. 2012, Donkor et al. 2014). ANNs and their performance for medium to long-term forecasts have not been widely researched.

ANNs were applied here for non-linear regression fitting. For this analysis, feed-forward neural networks with one hidden layer of ten neurons, were used. A feed-forward neural network was selected as a means to map the desired output, the flow rate, based on the input variables discussed above. One hidden layer of ten neurons was selected by trial and error during the analysis. The Levenberg-Marquardt back-propagation training algorithm was applied to update the weights for the network based on the input and output data supplied. The input data set was randomly divided into training (70%), validation (15%) and test datasets (15%). The training set was used to train the network. Training continued as long as the network continued to improve as compared with the validation data set. The test dataset provided a completely independent measure of network accuracy (Matlab 2014). Networks were re-trained based on their performance outputs until a satisfactory performance was reported. The trained networks were then saved for re-application on new data to forecast future flow rates.

### Table 2. Input variables for regression models for DCC and WW valves.

| DCC ID | Input Variable | WW ID | Input Variable |
|--------|----------------|-------|----------------|
| D1     | Quarter        | W1    | Quarter        |
| D2     | Unemployment (%) | W2   | Welsh Regional Unemp. Rate (%) |
| D3     | Population Rate (%) | W3   | Welsh Regional Population |
| D4     | Participation Rate (%) | W4   | Ave. Household Water Bill (£) |
| D5     | Irish Construction Index | W5   | Welsh Construction Index |
| D6     | House Builds   | W6    | House Builds   |
| D7     | Leakage rate (%) | W7    | Leakage Rate (Ml/d) |
| D8     | Ave. Temperature (°C) | W8    | Ave. Temperature (°C) |
| D9     | Max. Temperature (°C) | W9    | Max. Temperature (°C) |
| D10    | Min. Temperature (°C) | W10   | Min. Temperature (°C) |
| D11    | Total Rainfall (mm) | W11   | Total Rainfall (mm) |
| D12    | Ave. Rainfall (mm) | W12   | Ave. Rainfall (mm) |
| D13    | Ave. Rel. Humidity (%) | W13   | Ave. Rel. Humidity (%) |
| D14    | Ave. Vap Pressure (hPa) | W14   | Ave. MSL Pressure (hPa) |
| D15    | Ave. Sunshine (Hrs) | W15   | Ave. Cloud Base |
| D16    | Total Sunshine (Hrs) | W16   | Ave Global Radiation (kJ/m²) |

Flow rate variation and longer-term socio-economic trends such as changes in the rate of unemployment, regional population, the amount of construction, and the annual change in leakage rates from the water supply mains in question. It also allowed for the investigation of long-term flow rate changes with changes in climatic variables, such as average temperatures, maximum temperatures and average rainfall.

The independent predictor variables used for the initial MLR model for both the DCC valves and the Welsh Water (WW) valves are detailed in Table 2. Average flow rates at each valve for each quarter were used as the dependent variable for this analysis. Quarterly datasets were available for many of the socio-economic variables, however, the leakage rates and population data were available on an annual basis only. For this study, annual data was linearly interpolated to a quarterly basis as has been adopted in previous research (Babel and Shinde 2011).

### 2.5. Artificial neural networks

ANNs were also applied for the long-term forecasting of flow rate at each valve. The models developed in this study differ from those applied to predict municipal water demand in the previous investigations in two key ways. Firstly, the ANN model developed in this research forecasts water demand at specific

Figure 2. (A) Annual average diurnal flow rate (m³/hr) at V4 (left) and at (B) V7.
2.6. Future scenarios

Future scenarios for flow rates and hence MHP power generation potential were predicted for two of the valves studied. The characteristic MLR equations for each valve were used. Forecasts for the related input data were required. Population forecasts as published by the CSO were obtained for the Dublin region. Mid-year population projections were also obtained for Welsh local authorities up to the year 2036 as produced by the Welsh Government Knowledge and Analytical Services.

The impact of climate change in Ireland and the UK has been estimated to include average seasonal temperature increases by between 0.75 °C and 1.0 °C by 2020. By the 2050s, temperatures were estimated to increase by 1.4 °C–1.8 °C, with the greatest warming occurring during the autumn. By the 2080s, increases were forecasted to be in the range 2.1 °C–2.7 °C (Sweeney, 2001).

3. Results

3.1. Hourly data investigation

The results of univariate linear regression models between each of the hourly input variables and the hourly flow rate of valves V1 to V5 are detailed in Table 3. These regression models reported very low correlations between the hourly flow rates and climatic variables such as the hourly temperature, the amount of rainfall or the relative humidity. The reported $R^2$ values for each of the individual cases was less than 10%, with some as low as 0.1%. In Table 3 it can be seen that though climatic variables such as the amount of sunshine and the temperature explain up to 9% of the variation, the most significant contributor to the overall regression model for all valves was the hour of the day.

An investigation into the change in daily flow rate patterns at these valves was then undertaken. As shown in in Figures 2(A) and 3(B), it was found that though the magnitude of the average annual flow rate varied year-on-year, the daily demand profiles did not vary significantly between each year.

Further analyses of the average demand patterns on each day of the week showed that for many of the valves, different demand patterns were evident on weekdays versus weekend days (See Figure S3(a) for valve V9 (Rialto) and S3(b) valve V10 (Slievebloom)). Valve V9 showed decreased peak flow rates on weekends, whereas valve V10 showed increased peak flow rates on weekends. This was due to the local demands of the areas. Valve V10 was a largely residential area located further from the city centre than valve V9. Valve V9 had more businesses and shops in the local area which would see more water usage during the week. Furthermore, it was located near a large hospital with a university campus, and there would be many students living in the area who may commute to other parts of Ireland for weekends, further reducing the weekend water demand.

From this exploratory analysis of hourly flow rate conditions, it was decided that the long term forecasting model to be developed should predict an average flow rate. A demand profile based on the average demand pattern of the most recent year of data could then be applied to this average flow rate, for the approximation of the diurnal flow conditions into the future. Weekday versus weekend demand profiles could also be applied for accurate estimation of the differing demand variations.

3.2. Multiple linear regression

A correlation analysis was undertaken between the independent variables (see Table 2) and the flow rate at each valve. Backward stepwise linear regression was employed to ascertain the best fit model. When any two variables were highly correlated with each other (greater than 0.85), one of the variables was removed from the model.

Table 4 details the model performance data for the best-fit models (Table S1 shows the final independent variables selected in each model). All of the models presented reported $p$-values of less than 5%, indicating statistical significance of independent variables. Some models reported relatively high $R^2$ values, the Brunswick Street PRV (V2) model for example reported an adjusted $R^2$ of 66.8%. This model reported highest correlations with population and the number of houses built in Dublin. The actual and fitted curves for V1 and V4 are plotted in Figure 3. Though the model of best fit for V1 was found to explain only 36.9% of the variance, it can be seen on the fitted plot that the model has predicted the general trend. Valves V2 and V4 reported the highest adjusted $R^2$ values of all the MLR models at over 66%. The MLR models picked up on broad increasing trends in flow rate, however they did not accurately predict the peaks and troughs in flow. For three of the poorer performing models at V12, V15 and V16, a smaller number of observations were used as model inputs. This may have led to the poorer explanation of variance at these valves.

3.3. Artificial neural network

All of the ANN models out-performed their equivalent MLR models. The superior performance of ANNs in this application can be attributed to their ability to identify non-linear trends and relationships between the input and target data supplied. An overview of the model statistics for each ANN model is provided in Table 4.

Similar to the MLR model results, low correlations were again found for valves V3 and V12. The actual and fitted values for V1 and V4 are again plotted for illustration in Figure 3. The ANN models were found to more accurately fit the data for these valves, both the general trend and the peaks and troughs.

3.4. Future scenarios

The two sites with the highest $R^2$ values were selected for future scenario analysis, as these would forecast most accurately based
on the correlations found. These were: the Brunswick St PRV (V2) and the Cookstown B Reservoir valve (V4). The linear regression equation for the Cookstown B Valve (V4) was found to increase linearly with the Dublin population as shown in Equation 1.

\[ y = -3522.7 + 4.6597 \times \text{Population} \]  

(1)

Using the CSO population predictions for Ireland as described earlier, future flow scenarios for V4 were predicted and plotted in Figure 4, with the 2012 average diurnal demand pattern applied. As the population of Dublin increased in line with CSO predictions, flow rates in V4 were estimated to more than double the 2002 average flow rates.

\[ y = -572.33 + (0.55424 \times \text{Population}) + (0.043139 \times \text{Houses}) \]  

(2)

The characteristic equation for the Brunswick St valve (V2) was found according to Equation (2), where quarterly average flow rates \( y \) were predicted to increase with population and the number of new houses built. According to a forecast published...
overestimated the flow rates during the night hours, many of the points plotted indicate good correlation. The 2020 forecast showed a significant increase in flow rate at this valve, due to increased population and economic activity.

4. Discussion

The estimated design life of hydropower turbines is in the range of 20–25 years, with some turbines remaining in operation for even longer periods. Large fluctuations in flow rates over the life of a turbine may result in reduced efficiency and alterations in economic viability. From the hourly flow rate analysis conducted here, it was found that for some valves, e.g. V4, there was very little variation in the diurnal pattern over the ten years. The average diurnal flow pattern varied from between 98% and 105% of the average annual flow rate in 2002. This valve however is located at a reservoir and not within the distribution network, therefore would experience less variability. At valve V7 on the distribution network, more variability in the daily demand was found with daily flow rates varying between 65% and 130% of the average flow in 2002. Thus a MHP turbine designed to operate efficiently for the average flow in 2002 would have under-performed in many of the subsequent years, as found in other similar investigations (Sitzenfrei and Rauch 2015).

The importance of assessing the future variations in flow rate is therefore essential during the design and feasibility phase of MHP in WDNs. The rate of unemployment (D2), the population (D3), the rate of leakage (D4) and the number of houses built (D6) were found to be the most influential variables for long term changes in flow rate in Ireland. Population, the rate of leakage and the number of houses built were common in two different countries, Ireland and the UK.

Of the climatic variables tested, the most significant indicators of flow rate variation were temperature and rainfall. The average temperature and the maximum temperature were found to be influential for two DCC valves. This is likely due to the seasonal demands in those areas for the maintenance of local gardens, parks and sports grounds. In climates which experiences larger variations in temperature, e.g. hot or cold climates, climatic variables may play a larger role in future flow rate predictions.

Three of the Welsh valves reported significant correlations between the flow rate and the average household water bill. For example, at Pontypool valve (V14), the average flow rate was found to be influenced by the water price, population and the minimum temperature. Increases in price caused a decrease in average flows. Furthermore increases in the minimum average temperatures resulted in increased average flow rates. The best MLR model for V14 corresponded to Equation 3:

$$y = -94478 - (10.47 \times \text{Price}) + (1.0579 \times \text{Population}) + (12.109 \times \text{Min.Temp})$$

(3)

At V14 the average flow rate in quarter 3 of 2012 was 380 m$^3$/hr. The average household water bill in 2012 was £178. If water prices increased by 5%, it was estimated that the average flow rate would reduce to 312 m$^3$/hr. In reality water is a necessity for households and businesses. While demand will respond to marginal changes in prices, the larger the price hike the more inelastic demand becomes, as users still require a minimum supply regardless of the price. The current approach does not account for the inelasticity of demand.

by Morgenroth (2014), due to increased demand for housing in Ireland and a shortage of available housing stock, it is estimated that 18,000 new houses are required to be built in Ireland annually between 2014 and 2020. The majority of these, between 13,000 and 15,000 are estimated to be required for the Dublin region. A 2020 forecast for this valve was estimated based on 3750 houses to be built per quarter. Again using the CSO forecasted population for 2020, enabled the forecasted 2020 diurnal flow rate at valve V2 to be predicted as shown in Figure 5.

Also in Figure 5, a calibration of the regression model was undertaken using actual flow data for 2013 at this valve, obtained from DCC. The 2013 quarter 1 average daily flow rate was predicted using the published numbers of houses built in the Dublin City Council region, and the published population estimates for Dublin for 2013. The daily average demand pattern for 2010/2011 was applied to this forecasted average flow rate.

As can be seen in Figure 5, the regression model developed using the 2002–2012 flow data has allowed for a good approximation of the 2013 quarter 1 flow rate. Though it has slightly overestimated the flow rates during the night hours, many of

Figure 4. Annual average diurnal flow rates at V4 with 2016, 2021, 2026 and 2031 flow rate forecasts plotted.

Figure 5. The average 2010/2011 and 2013 diurnal flow rates at V2 with the average MLR forecast diurnal flow rates for 2013 and 2020 plotted.

Table 5. Annual energy generation (MWh) from 2003 to 2020 forecast.

|            | 2003 | 2008 | 2012 | 2020 |
|------------|------|------|------|------|
| V2: Brunswick St PRV | 71.83 | 184.84 | 146.29 | 381.06 |
| V7: Poplar Row PRV | 139.28 | 172.57 | 151.55 | 176.08 |

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Three of the Welsh valves reported significant correlations between the flow rate and the average household water bill. For example, at Pontypool valve (V14), the average flow rate was found to be influenced by the water price, population and the minimum temperature. Increases in price caused a decrease in average flows. Furthermore increases in the minimum average temperatures resulted in increased average flow rates. The best MLR model for V14 corresponded to Equation 3:

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Further significant correlations with the minimum temperature and an increased flow rate were also found for three of the DCC valves. For two of these three valves, correlations with the leakage rate were also found.

The ANN models were found to more accurately predict the water flow variation based on the input variables. This is most likely due to their ability to identify non-linear trends in the data. This would be especially relevant with climatic variables, as the relationships between climatic variables such as temperature and rainfall with urban water demand may be non-linear (Billings and Jones 2008).

Though the ANN models outperformed the MLR models, these required more input data for the purposes of future forecasts. All of the ANN models were developed using the available data, varying from 6–10 years of quarterly inputs. In order to forecast using these ANN networks developed, a full 6 to 10 years of input data is required to be passed to the ANN. To predict flow rates for ten years of data for the Cookstown valve for example, the equivalent ten years of population estimates must be passed to the network. Population forecasts are usually made for every five years, and as such the intermediate years would need to be either linearly interpolated or estimated. The increased amount of assumptions required using ANNs would reduce the accuracy of the forecast.

Flow rates were forecast for future scenarios, taking future climate change factors, population and economic changes into account. A comparison of the change in the potential for power generation at V2 and V7 are detailed in Table 5. Both valves were estimated to see power generation potential increases by 2020, due to increased flow rates. For the V2 case, this flow increase was primarily due to a forecast increase in housing construction for the Dublin region (Morgenroth 2014). For V7, flow rates increases were found to be linked to the leakage rate in DCC mains, and decreases in the level of unemployment in Dublin. With unemployment rates in Ireland predicted to decrease to 7.5% by 2020, average temperatures to increase as forecast (Sweeney, 2001) and assuming DCC leakage rates are reduced to 20% by 2020, the average quarterly flow rate at V7 was forecast to increase.

An MHP turbine installed in place of the PRV at Brunswick St in 2003 was estimated to have the potential to produce 71.8 MWh of energy, based on the average quarterly flow rates and assuming a conservative constant system efficiency of 65%. This power output potential was shown to increase and decrease significantly within the 10 year period of historical data and was predicted to increase further by 2020. The implications of designing an MHP turbine for the WDN based on the 2003 flow rates only are clear when we examined the changes in flow that occurred in subsequent years. The efficiency of such a turbine would not be an optimum for much of its design life and the turbine would not deliver the same return on investment that would be predicted using only 2003 data. As such it is important to i) take account of as much historical flow data available at MHP water distribution sites as possible during turbine design; and also to ii) make predictions on the future growth or decline in flow rates at a site over its design life.

5. Conclusions

Both MLR and ANN analyses were applied and provided methods of forecasting average quarterly flow rates at valves within WDNs. MLR analysis provided an indication of the level of correlation between water flow rates and the independent variables. The most significant relationship, common to both the Irish and UK data, was the relationship between water flow rates and the local population. Water price was shown to have a significant influence on flow rates at three of the four Welsh valves. It is recommended that MLR be used during feasibility studies of new hydropower projects planned within WDNs. MLR has been shown to provide an indication of long-term changes in flow rates, due to economic and climatic changes.

A key contribution of this paper’s findings is that the MLR models could be used to forecast future average flow rates at potential hydropower locations. This forecasted average flow rate, combined with the application of the characteristic average diurnal water demand pattern for that valve, enabled the forecasting of flow rates and hydropower generation capacities. A number of different future scenarios could be tested as part of the sensitivity analysis, such as large population growth or large increases or decreases in unemployment.

For all future scenarios modelled, flow rates were predicted to increase by 2020, largely due to the forecast increase in the populations in the study areas within both Ireland and the UK. Growth in flow rates would increase the hydropower generation capacity at these sites. However, with large increases in water demand, new water resources may need to be developed, which may render certain parts of the network obsolete. This risk should also be noted at the feasibility stage of any hydropower project. Overall, MLR and ANN analyses were found to be good methods for approximation of flow rates at potential hydropower locations within WDNs.

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Disclosure statement

The authors have no conflict of interest to declare, financial or otherwise.

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