Municipal Water Demand Forecasting in the Short and Long Term with ANN and SD Models

by

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Abstract

Decision makers require accurate estimates of water demand for the planning and operation of water resource systems. Short-term water demand forecasting can offer immediate information to assist daily or weekly operation while accurate long-term forecasting allows water utilities or governments to make informed decisions for water management and planning. These needs have prompted the development of statistical regression analysis and time series models for water demand forecasting over the past decades. More recently, artificial neural networks (ANNs) have increasingly been used to forecast short-term water demand due to their high prediction accuracy and independence from statistical assumptions. System dynamics (SD) models are superior for long-term forecasting because of their structure-based approach that permits detailed simulation of individual end uses, and the ease of running multiple scenarios for assessment of alternative management policies. This study developed both short-term and long-term water demand forecasting models for Edmonton, Canada, using ANN and SD models. The first part of the work explored the capability of ANNs for forecasting short-term – daily and weekly – water demands. Model development followed the conventional approach that includes model configuration, training, and testing for the study area; the performance of the best resulting ANNs was also compared to results from a conventional regression approach. The second part of the work produced a novel hybrid model composed of an ANN, several regression models and a system dynamics model for projection of long-term water demands. Several scenario groups were built based on the validated model to 1) investigate the relative importance of key demand drivers to long-term demands: population growth, climate change and policy implementation, and 2) assess the combined effect of multiple drivers to provide useful best-case and worst-case information, such as estimates of water demand from 2020-2100 and the year that water demand will double,

of interest to water managers and decision makers for water demand management and planning. The study demonstrated the excellent ability of ANN for short-term forecasting, and the feasibility and accuracy of hybrid system-dynamics/data-driven models. The optimum ANNs for daily and weekly forecasting (with $R^2 = 0.92$ and $R^2 = 0.89$) consistently outperformed the conventional regression models. For short-term water demand forecasting, previous water demand was found to be the most effective predictor. Daily and weekly forecasting were found to depend relatively more on maximum air temperatures and mean air temperatures, respectively. Precipitation predictors were important only in conjunction with air temperature data, and precipitation amount was a better predictor for the Edmonton and region water demand than precipitation occurrence. For long-term forecasting, the hybrid model significantly outperformed an earlier SD model developed for Calgary over the whole simulated period, with an NRMSE that decreased significantly from around 7.9% to 4.7%. Simulations revealed that population growth produced the greatest change in water demand by 2100. Even with a slow population growth rate, the water demand under current policy conditions and medium climate change (RCP 4.5) increased by 162% by 2100, with doubling at 2079. The difference in water demand between high and low population growth scenarios was 20%, while climate change alone produced the least significant change – the difference between the high and low climate change scenarios was a 12% difference in water demand. The implementation of xeriscaping, greywater reuse and a best technology decreased the water demand by 17% compared to the reference scenario by 2100. Under the best-case scenario, with low population growth, low climate change and implementation of three water conservation policies, water demand doubled 30 years later than in the worst case, which included both high population growth and climate change, and no additional water conservation policies implemented.

Preface

This dissertation is original work by Hanyu Liu. The literature review in Chapter 2, description of study area in Chapter 3, models and user interface as well as programming scripts referred to in Chapter 4, modifications shown in Chapter 5 and concluding analysis in Chapter 6 are my original work with the assistance of Dr. Evan Davies. Heather Zarski and Spencer Gerlach in EPCOR Water Services Inc. contributed to data collection in Chapter 3. The hybrid system dynamics and artificial neural network model in Chapter 5 builds on previous model development work conducted by Kai Wang. Chapter 5 includes material adapted from a paper expected to be published in 2020.

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Chapter 1 Introduction

1.1 Problem Statement

Water utilities make operational decisions on short time scales of hours to weeks to meet municipal demands. Short-term water demand forecasts help to balance the water supply amongst urgent water needs, plan maintenance and operating schedules for system infrastructure and inform decisions about water levels and drawdowns for reservoirs (Billings & Jones, 2008). Short-term water demand forecasts also aid in accurate decision making, such as when to implement regulatory water use restrictions in times of water stress or drought (Herrera et al., 2010), how to manage storage tanks that store volumes of water, and when and how much chemicals to add for treatment processes, as well as for estimates of energy use at treatment plants (León et al., 2000). Traditionally, operators estimated water demand according to their experience and the previous water demand (Zhou et al., 2002); however, changes of water demand over short term depends on both water consumption requirements and habits of residents, businesses, and institutions, and on weather conditions. Reliable short-term water demand forecasting models are therefore requisite to water utilities, permitting an efficient management of water supply, water storage and the related equipment.

Many water utilities across North America, including EPCOR Water Services Inc. (EWSI) of Edmonton, Alberta, have observed declining water consumption per residential customer trends over the past three decades (EWSI, 2018). For long-term planning, such reductions in use have financial implications since water utilities typically bill for water use on a per-unit-volume basis (Tsur, 2005). In addition to ensuring the economic sustainability of the utility itself, reliable long-term water demand forecasting is also critical for management of water resources to avoid water scarcity – a condition where water resources are inadequate to meet the long-term requirements

(Van Loon & Van Lanen, 2013). Based on long-term predictions, policymakers such as water utilities and government agencies formulate water management strategies and infrastructure development in advance to meet the demands of their customers or citizens into the future (Cosgrove & Loucks, 2015).

Accurate prediction of water demand is therefore important for both short-term (operational) and long-term (planning) aspects of urban water management. However, sophisticated research models for short-term forecasting have not commonly been applied by water utilities because of the difficulty of their development and use. Further, few studies have been conducted for long-term municipal water demand projection, and fewer still have simultaneously addressed population growth, climate change, and water conservation policies. To address both sets of shortcomings, two models were developed as described below, the first for short-term operational projections, and the second for long-term planning applications. In addition to model development, the study also addresses both short-term and long-term forecasting to permit a comparison of alternative modeling methods: artificial neural networks, regression models, and system dynamics models.

1.2 Research Objectives

The study has two main research objectives that are intended to provide useful tools and investigate key drivers for both short-term and long-term water demands in Edmonton:

1. The development, application and analysis of short-term, operationally-focused water demand prediction models; and,
2. The development and analysis of long-term, planning focused water demand prediction models.

The first objective focuses on the capability of ANNs to forecast daily and weekly water demands, with a comparison of two types of ANNs (BPNN and ELM) with a conventional approach (MLR) commonly used to predict water demand. This objective requires a detailed exploration of ANN structure and identification of the best-performing model for daily and weekly simulation. The most effective variables in short-term water demand forecasting will be identified and applied to give water utilities a better indication of the correlation between weather predictors and water demand.

The feasibility, benefits and accuracy of a hybrid structure-based system dynamics and data-driven (ANN and regression models) model will be examined for long-term water demand forecasting. Three critical water demand drivers – population growth, climate change and water-saving policy – will be investigated in terms of their relative and combined importance in long-term water demand forecasting. Further, future water demand scenarios under multiple conditions will be simulated to help water resource managers realize the potential change of water demand and develop corresponding water infrastructure and management strategies.

1.3 Thesis Structure

Following the brief description of this research in Chapter 1, Chapter 2 presents an overview of commonly used water demand forecasting techniques such as the conventional regression approach, time series models, computational intelligence approaches as well as previous applications of ANNs and SDs. The study area in terms of population, water treatment plants, water supply and streamflow in Edmonton, and a complete list of data sources are presented in Chapter 3. Chapter 4 describes essential components of ANN model and then introduces the training and optimization process. The rest of the chapter then describes the evaluation of the simulation accuracy of ANN and presents the interactive user interface developed for use by EWSI based on the obtained ANNs. Chapter 5 describes the hybrid SD-ANN-regression model as well as its component parts, compares its performance against the original SD model, and introduces scenarios of future water demand for analysis with the model under potential population growth, climate change, and water conservation policy implementations. Chapter 6 presents the validation results for models as well as an analysis of the relatively important factors in both short-term and long-term forecasting. Conclusions are then drawn in Chapter 7, study limitations are described, and possible future research directions are provided.

Chapter 2 Existing Approaches of Water Demand Forecasting

Potential water scarcity under mounting population and water demand has become a common concern (Cosgrove & Loucks, 2015). An important criterion to evaluate the water scarcity condition of one region is the balance between water supply and water demand. Water demand forecasting allows decision makers to realize possible trends of water demand ahead of time, evaluate the possibility of meeting available water resource demands, and further make corresponding planning and management efforts to avoid consequences of water scarcity (Butler & Ali Memon, 2006). With the increasing concern of water scarcity, water demand forecasting has become crucial in water management and sustainable design, which has driven the development of water demand forecasting modeling (Anele et al., 2017).

The purpose of a forecasting model determines the necessary model time step, which then determines the capabilities and applicability of the resulting model. Models with small time steps, often from hourly to seasonal, focus on investigating changing patterns in demand over the desired period such as the preferred water use time when peak demand occurs as well as fluctuations in demands with the seasons. Such models can be used to assist with regular water operation, reservoir management , and water treatment regulation (Billings & Jones, 2008). Long time-step models, which are often focused on annual variations, allow users to assess potential changes over a long period, which helps with planning and management related to significant concerns of the public and water utilities related to water prices, infrastructure development and fixture updates (Donkor et al., 2014; Qaiser et al., 2011; Qi & Chang, 2011).

Models require input variables, or “explanatory variables” to produce their output in terms of projected demands. The selection of explanatory variables for a water demand prediction model depends on the desired time scale (Shabani et al., 2016). For short-term forecasting, weather conditions such as temperature, pan evaporation, rainfall, wind speed, relative humidity, and precipitation affect water demand significantly (Praskievicz & Chang, 2009). Researchers tend to separate time series into the winter (frozen, or low demand) season and the summer (growing, or high demand) season, and separate residential indoor water uses and outdoor (lawn, garden and other) water uses, in order to investigate the effect of weather (Zhou et al., 2002). Long-term changes in water demand could result from industrial development and urbanization (Arnell & Liu, 2001), as well as burgeoning issues such as shifting weather patterns caused by global climate change and population growth. Climate change (Dawadi & Ahmad, 2013) and population growth (PAI, 2012) bring great uncertainty to water availability, and are a common concern worldwide. Therefore, the investigation of their impact on long-term water demand predictions should receive greater attention.

Traditionally, historical patterns are usually the only explanatory variables used by water utilities to predict future water demands; these generally failed to integrate the factors that drive changes in their values (Rahman et al., 2016). However, the increasing numbers of regions suffering water scarcity have raised the awareness of policymakers and led to implementation of advanced statistical techniques that include diverse predictors of water demand. Table 2-1 summarizes the variables that water demand forecasting models have commonly used over the last two decades as well as their time scales, organized by time scale and then chronology. Clearly, a wide range of methods can be used for municipal water management and modeling, with the selection depending on modeler skill, available resources and data, and accuracy requirements. An overview of previous modeling techniques such as time-series analysis, regression analysis, artificial intelligence, and system dynamics with an emphasis on water demand will be provided in the next section, with a focus on their time scale and socio-economic connections.

Table 2-1 Determinants in previous water demand forecasting research

Reference		Determinant	Time Scale	Method
1	Herrera et al. (2010)	Temperature, wind velocity, rain, atmospheric pressure and delayed demand	Hourly	Support Vector Regression (SVR) models, Random Forest, Multivariate adaptive regression splines and Projection pursuit regression
2	Brentan et al. (2017)	Air temperature, air humidity, rainfall and wind velocity	Hourly	Hybrid model: Support Vector Regression and Adaptive Fourier Series)
3	Zhou et al. (2002)	Maximum temperature, daily precipitation and Class A pan evaporation	Hourly and Daily	Time Series
4	Jentgen et al. (2007)	Temperature, precipitation, and delayed demand	Hourly and Daily	ANN, Time Series and Linear Regression
5	Adamowski et al. (2012)	Precipitation, temperature, and delayed demand	Daily	Wavelet transformed-artificial neural network (WA-ANN), multiple linear regression (MLR), multiple nonlinear regression, autoregressive integrated moving average (ARIMA) and ANN
6	Mouatadid & Adamowski et al. (2017)	Temperature and precipitation	Daily	ANN, SVR, ELM, MLR
7	Seo et al. (2018)	Delayed water demand	Daily	Variational Mode Decomposition (VWD), ANN and extreme learning machine (ELM)
8	Bougadis et al. (2005)	Temperature, rainfall, the occurrence of rainfall, and delayed peak demand	Weekly	Regression, Time Series and ANN

9	Wang & Davies (2018)	Population, temperature, rainfall, policies and price	Weekly	System Dynamics
10	Brekke et al. (2002)	Seasonal indictors, weather variables and water price	Monthly	Stepwise Regression
11	Polebitski & Palmer (2010)	Density, built structure size, lot size, household size, number of houses, income, price, temperature, precipitation and policy	Bimonthly	Linear regression
12	Msiza et al. (2008)	Delayed demand and population	Annual	Support vector machine (SVM) and ANN
13	Lee et al. (2010)	Residential water consumption and population density	Annual	Bayesian moment entropy approach
14	Li & Huicheng (2010)	Population, GDP, temperature, greenery coverage and delayed demand	Annual	Multiple linear regression and fuzzy neural network based on HP filter
15	Wang et al. (2016)	Population, price, climate, lifestyle, technologies	Annual	Water balance models
16	Wang et al. (2018)	Population, meteorological variables, lifestyle and technologies	Annual	System Dynamics
17	Schleich & Hillenbrand (2019)	Price, income, household size, age, population density, number of commuters and delayed demand	Annual	Asymmetric response model

2.1 Conventional Models in Water Demand Forecasting

An increase of conventional statistical modeling for water demand projection, especially the application of multiple regression and time series, was observed over the decades up to 2000 (Anele et al., 2017), and such models continue to be widely used. Time series (TS) analysis is a common method for water demand forecasting (Alhumoud, 2008; Zhou at al., 2000), since these models are practical and straightforward to develop and require no knowledge of the internal processes in a system. Various types of TS models have been used in water demand forecasting, including autoregression (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) (Amponsah et al., 2015; Billings & Jones, 2008). Amponsah et al. (2015) recently applied all five of the above types of models for water demand forecasting using historical water consumption data for the Hohoe Municipality of the Volta Region and concluded that the best-performing model was ARIMA.

Temporal variations occur in the real world, which give rise to limitations in univariate time series modeling, as Tong (1983) explains. The main drawback of the TS approach is that it assumes the water demand will retain the same pattern with the past and no alternatives will be applied such as extreme weather, new policies, or price adjustments. Such models have a weak ability to distinguish the seasonal variations of water demand in daily to monthly forecasting or adapting additional policies in long-term forecasting, which may produce less accurate predictions (Donkor et al., 2014; Qi & Chang, 2011)

Regression modeling is also a popular and simple technique for water demand forecasting (Jain et al., 2001; Uca et al., 2018). Regression models represent the relationship between explanatory variables and the response variable, so it has been widely used to explore the effects of possible determinants of water demand (Anderson et al., 1980; Brekke et al., 2002; Lee et al., 2010; S. Polebitski et al., 2011). The temporal trend in water use is correlated with socio-economic and climate factors (House-Peters & Chang, 2011). For short-term (hourly to weekly) scales when socio-economic factors hardly change, diverse meteorological factors such as temperature, precipitation, relative humidity, and wind speed have been used as determinants in linear regressions for water resources forecasts (Adamowski & Karapataki, 2010; Bougadis et al., 2005; Jain & Ormsbee, 2002; Msiza et al., 2008). For the medium to long-term scale, socioeconomic factors such as water rate, income, population, and urban share tend to be combined in regression models (Billings & Jones, 2008; Hug, 2015). The primary defect of regression models is that they regard all relationships as linear, while in reality, the problems are often necessarily nonlinear (Brekke et al., 2002).

In previous research, regression models have sometimes been used for comparisons with other advanced techniques. For example, Jain & Ormsbee (2002) compared linear regression models and artificial neural networks for weekly water demand forecasts using maximum temperature, rainfall, water demand of the previous week, and rainfall occurrence as inputs. They concluded that ANNs consistently outperform regression models. Further, the linear relationships in regression models are simply represented as time-invariant constants in equations, which are not able to respond to the potential changes such as policy alternatives in the future (Donkor et al., 2014). Therefore, results from regression models are inappropriate for long-term water management.

2.2 Artificial Neural Network Models

Artificial Neural Networks (ANNs) are a computational intelligence technique that mimics the behavior of biological neural systems to find nonlinear trends or patterns between explanatory variables and desired variables from complicated data (Eluyode & Akomolafe, 2013). Specifically, an ANN can extract unknown nonlinear relationships between explanatory variables and desired variables in complex problems that are difficult to generalize through common equations (Hsu et al., 1995). The development of an ANN does not require prior knowledge of the statistical characteristics of the raw data such as the general fluctuating pattern and seasonal variations, which are extracted by the internal learning process of ANN (Burke, 1991; Maier & Dandy, 1996). Finally, ANNs excel over conventional models in the extraction and modeling of complicated and nonlinear patterns, which allows them to be applied to most real-world problems that have nonlinear relationships between drivers and the resulted changes (Jentgen et al., 2007). A detailed description of ANN model development is provided in Chapter 4.

ANNs are data-driven and relatively straightforward to develop where patterns between inputs and outputs can be derived by optimizing the weights and bias associated with the connections between neurons (Jeong et al., 2018; Taormina & Chau, 2015; Zhang et al., 2001). They have been used widely for multiple kinds of problems including classification, clustering, pattern recognition and prediction (Abiodun et al., 2018). Successful applications of ANNs covering many areas of both science and engineering suggests its applicability and effectiveness for water demand modeling, particularly since water demand and weather variables over a short period tend to have a nonlinear relationship. For example, Jain et al. (2001) established ANN models for weekly water demand projection using weather parameters, and also compared their results with values from regression models and time series models. The input data was composed of maximum temperature, amount of rainfall, the occurrence of rainfall and water demand of the previous day. They found that the ANN models consistently outperformed the conventional methods. Adamowski & Karapataki (2010) applied ANNs and conventional approaches for peak daily urban water demand forecasting, which also indicated the excellent prediction ability of ANNs. Among TS, regression model and ANNs, ANNs with rainfall and temperature data as inputs consistently provide the best predictions for weekly total water demand and peak water demand (Bougadis et al., 2005; Jain et al., 2001). A similar conclusion was reached for hourly forecasts (Jentgen et al., 2007). An alternative approach is hybrid approaches, which are composed of ANN and other types of models and have been developed by researchers in order to improve forecast accuracy (Aly & Wanakule, 2004; Li & Huicheng, 2010).

Although the simulated results of ANNs for short-term forecasting can be very accurate with R^2 as more than 0.85 in Mouatadid & Adamowski (2017) and Tiwari et al. (2016), and with mean relative errors as 1.58% in Yin et al. (2018) , they are not well-suited for projections of long-term trends. For the long-term perspective, various factors contribute to the change of future water demand, including policies, population, infrastructure, technology, human behavior, and climate. ANN models do not explicitly model these components, which are not specifically represented in the historical data, but instead provide a projection of single output (water demand) based on historical data inputs. Consequently, the outputs of those studies without accounting for the potential changes of water systems caused by non-historical population growth, climate change, and policy implementation are not reliable for water resource management and planning (Khatri & Vairavamoorthy, 2009).

2.3 System Dynamics Models

System dynamics is a computer-based simulation approach developed by Jay Forrester (1961) that improves understanding of the structure of a system and of its complex behaviors over time (Elsawah et al., 2017). SD models attempt to replicate the behaviors of real-world physical structures and processes through the representation of stock and flow dynamics, delays, and feedback structures. In the real world, visible events result from a series of invisible interactions and feedbacks, such that external behaviors of a system stem from internal interactions (Davies & Simonovic, 2010). Different from most data-driven models that extract a single result from the data used, SD models emphasize identifying the internal connections in a system and responding to the future management actions based on the feedback structure (Simonovic, 2012). As an iterative approach, it is easy to update the conditions of population, climate and water-saving policy at any time step. Further, they also provide a clear interpretation of the systems and comprehensive results for users (Wang & Davies, 2018). Thus, SD models have been successfully applied in many fields to address social, economic, physical and biological problems (Sterman et al., 2000) as well as water resource management problems (Chintalapati et al., 2019; Davies & Simonovic, 2011; Duran-Encalada et al., 2017; Winz et al., 2009; Zare et al., 2019).

SD also provides important capabilities for municipal water demand forecasting. Municipal water use can be divided into multiple specific end uses including toilets, showers, laundry, kitchen, leaks, outdoor lawn watering, commercial use, non-revenue use, regional use and others (DeOreo et al., 2016). SD models can simulate the specific individual end uses because of their structural modeling approach. The results of individual end-use demands from SD models can help water utilities or governments to understand the distribution of municipal water consumption by end use and therefore plan infrastructure expansion or policy updates in advance (Stave, 2003). From a long-term perspective, it is crucial in water resources management to integrate the social and economic components of the water system; otherwise, those ignored long-term socio-economic effects lead may to inaccurate simulation of future conditions (Klein et al., 2005). Water demands will potentially change into the future with climate change, increasing population, technology, and water management decisions (Pannell, 1997; Saltelli et al., 2008). SD models allow users to build scenarios and perform sensitivity analysis. Building scenarios means picturing multiple different possible future situations through altering the factors to be investigated, which is a commonly used approach to explore the effects of decisions and strategies, and the insights into cause-and-effect loops (Amer et al., 2013). Sensitivity analysis studies how the uncertainty in the inputs contributes to the uncertainty in a certain output, aiming to better understand the relationships between input and output variables in a system (Pannell, 1997; Saltelli et al., 2008). Through scenario development and sensitivity analysis, SD modeling is therefore an appropriate approach to evaluate the individual or combined effects of the drivers of change over the long term (Gober et al., 2011; Wang & Davies, 2018).

A key advantage of SD models is that they can be made to represent a number of different water end uses, and can therefore offer insight into the causes of changes in water demand. In contrast, regression models, TS models and ANN usually make predictions on general types of water demand such as total water demand or residential water demand (Gober et al., 2011). Ahmad & Prashar (2010) developed a detailed SD model for municipal water management with the simulation of residential end uses (i.e. kitchen, toilet, bath, laundry and outdoor), public use, commercial use, and industrial use. Wang & Davies (2018) also added regional use and leaks into their municipal water management model, which operates at a weekly time step and provides the most detailed long-term simulation of municipal demand available. The majority of the relevant research has focused on potential effects of changes in population or climate on aspects of municipal water management (Ahmad & Prashar, 2010; Amisigo et al., 2015; Parkinson et al., 2016; Rasoulkhani et al., 2018; Stavenhagen et al., 2018; Wang et al., 2018). Since limited research has focused on long-term municipal water management, a comprehensive model may significantly enhance understanding of potential changes in water demands and aid decision making for water management. However, such a detailed framework requires a large amount of data – for example, water demand records at a weekly or finer time step for different end uses, available water-saving policies, water demand per use and number of uses to support. The unavailability of important data usually requires modeling assumptions to be made, which may decrease the suitability of model predictions for decision making.

2.4 Summary

Water supply planning, and more recently water scarcity concerns, has led to the implementation of advanced forecasting techniques for water demand. Four widely-used modeling approaches were introduced in this literature review, including two conventional approaches (time series and regression analysis), and ANNs and SD models. The selection of models depends on the purpose of a forecasting model and its capabilities. Regression models, time series and ANNs have been successfully applied for short-term forecasting in numerous studies, which have found that ANNs consistently outperform the conventional models. Some ANN studies investigated the effectiveness of weather variables in predicting water demand and produced contrasting conclusions on use of the precipitation amount or precipitation occurrence.

For long-term water demand forecasting, the three models are less appropriate since they cannot respond to the potential changes such as policy alternatives in the future. In contrast, SD models can evaluate the individual or combined effects of variables that drive changes over the long term because of their "cause-and-effect" structures and modeling capabilities (e.g., scenario building and sensitivity analysis), which are suitable for long-term water demand forecasting. However, SD sometimes requires modeling assumptions due to the lack of important data, which may lead to the poor suitability of model predictions for decision making.

Chapter 3 Study Area and Data Sources

3.1 Study Area

Edmonton is the capital city of Alberta and the center of the Edmonton Metropolitan Region (see Fig. 3-1). Compared to other provinces in Canada, Alberta had the second-highest population growth rate from 2011 to 2016 with an 11.6% increase (Statistics Canada, 2016). Further, the city of Edmonton had a higher population change rate (14.8%) over 5 years than Alberta, while Canada witnessed only a 5% increase of population in the same period. It had a population of 972,223 people in 2019 (City of Edmonton, 2020) and is projected to reach a population of 2.2 million by 2044 (CRB, 2016).

Edmonton is located on the North Saskatchewan River (NSR), which is a glacier-fed river starting at the Canadian Rockies and ending at its confluence with the South Saskatchewan River near Prince Albert, Saskatchewan (NSRBC, 2017). The North Saskatchewan River provides raw water to two water treatment plants in Edmonton, E.L. Smith and Rossdale, which are owned, operated and managed by EWSI (EWSI, 2017). Fig. 3-2 shows their locations (EWSI, 2017). The water treatment plants implement a multi-step chemical and physical treatment to provide up to 680 ML/day of treated water for cities and communities in the Edmonton region water service area. The treated water serves residential, multi-residential, ICI (Industrial, Commercial, and Institutional) and regional use, whose distribution is shown in Fig. 3-3 (a).Detailed residential water use categories with percentages are shown in Fig. 3-3 (b); note that kitchen use includes water used for faucets and dishwashers. Regional water use represents the portion of water that EPCOR Water Service Inc. supplies under a wholesale agreement for use outside of Edmonton (see Fig. 3-4).

Daily per capita total municipal water use in 2018 was an average of 289 liters/person/day (L/p/d), ranging from 231 L/p/d, the minimum value in winter, to 401 L/p/d, the peak value in summer. The residential daily average per capita water use at 184 L/p/d was lower than the total municipal value. The value of average daily per capita total municipal water use is lower than the 2020 water use target proposed by the Alberta Urban Municipality Association of 341 L/p/d (AUMA, 2014). With the continued conversion to high-efficiency toilet and washing machines, Edmonton has observed a continuous decrease of per capita water demands and had already achieved the water use target by 2011 (EWSI, 2018).

The annual surface water allocations in the North Saskatchewan Basin totalled about 2 billion m^3 in 2007, which is approximately 27% of the total annual discharge of the NSR (EWSI, 2017). About 65 percent of municipal allocations are for the upstream sub-basins in which the study area (i.e., the Edmonton Metropolitan Region) is located, and these allocations significantly exceed the actual use. Further, of the volume withdrawn by EWSI, around 90% eventually returns from the wastewater treatment plants to the North Saskatchewan River as treated effluent (EWSI, 2017).

Finally, as noted above, water utilities typically bill for water use on a per-unit-volume basis, so that inaccurate predictions of water use have financial implications. Therefore, although the streamflow of the North Saskatchewan River can currently satisfy the water demand inEdmonton and the regional water service area, future demand is still necessary to project.

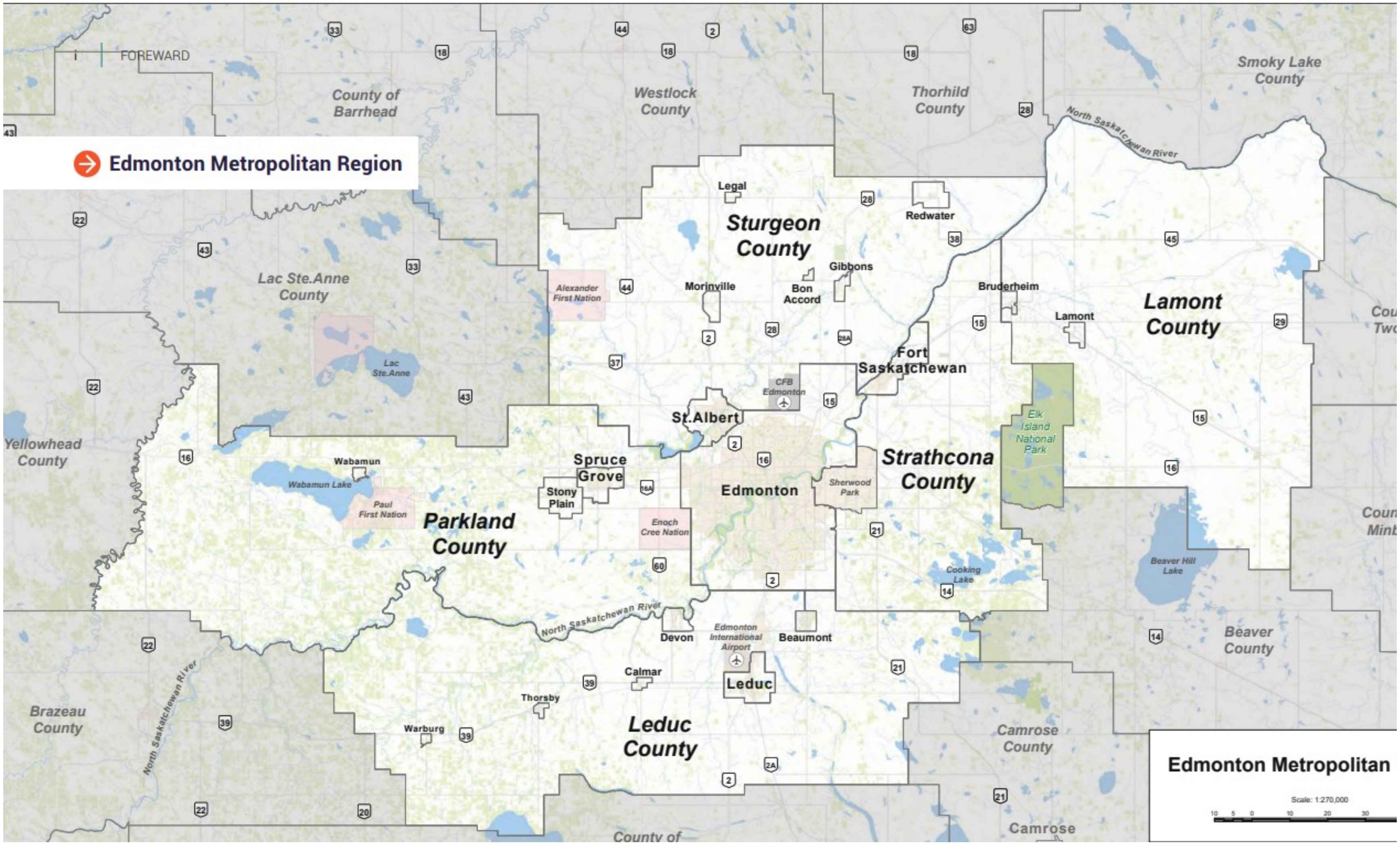
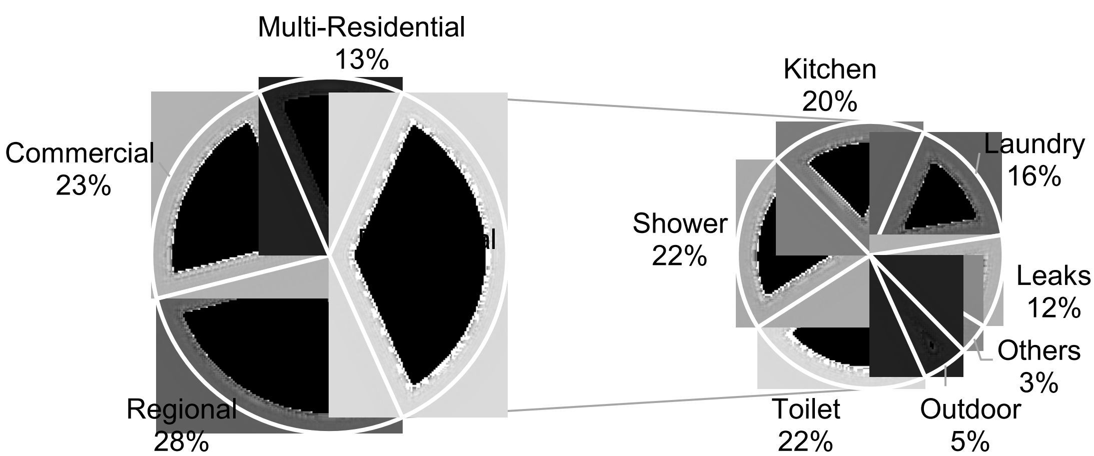


Fig. 3-1 Edmonton Metropolitan Region (EMRB, 2017)

Fig. 3-2 Water service areas for the Rossdale and E.L. Smith plants (EWSI, 2017)



(a) (b)

Fig. 3-3 Water use categories with percentages for Edmonton

Sources: (a) from EWSI; Outdoor in (b) from EWSI; Indoor categories in (b) based on DeOreo (2016). Shower category includes baths, and kitchen category includes all faucets (kitchen and bathroom) and dishwasher uses, based on Wang and Davies (2018)

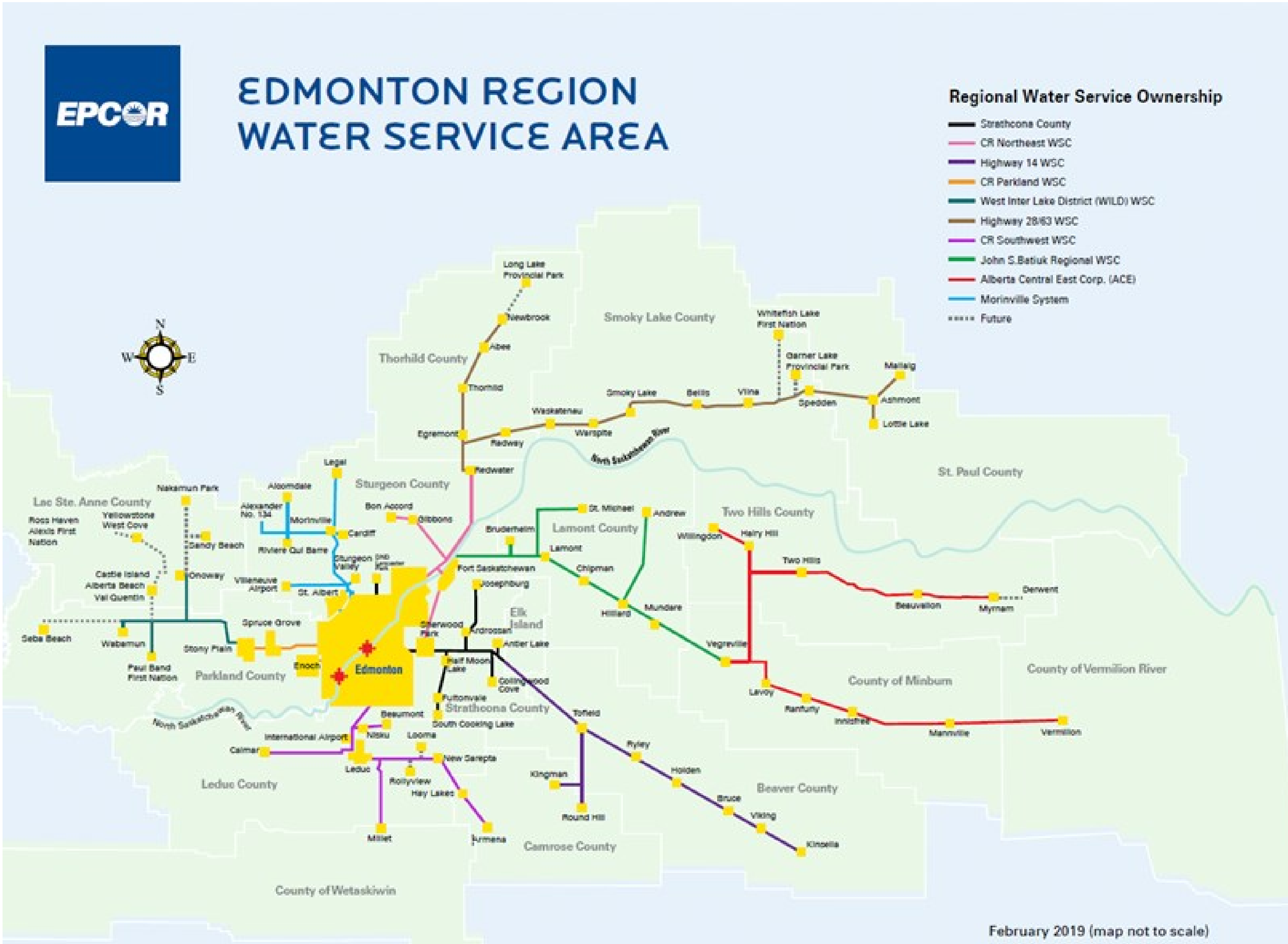


Fig. 3-4 Edmonton Region Water Service Area. (H. Zarski, personal communication, Jan 24, 2020)

3.2 Data Sources

Required data for short-term forecasting and long-term forecasting differ due to different drivers of change and different modeling techniques. In this study, the short-term analysis required 20 years of daily and weekly water-demand data and meteorological variables including maximum temperature, minimum temperature, average temperature, the amount of precipitation and the occurrence of precipitation for the city of Edmonton, Canada. The historical daily water demand from 1995 to 2018 for the Edmonton region water service area was provided by EWSI (Fig. 3-5). This data includes a downward "spike" of water demand around Christmas time each year, since many industries cease or reduce production during the holiday. These odd points may affect the results of modeling. Weekly observations can be aggregated from 7 days of daily data to produce corresponding weekly values (Fig. 3-6). In the time series records, water demand presents a significant difference between 600 ML/day in summer and 300 ML/day in winter every year. Water consumption during the winter period includes slight fluctuations while summer-period consumption varies significantly because of outdoor watering behaviors.

To simplify the forecasting process and because of data limitations, this study included air temperature and precipitation data for the short-term demand forecasts but excluded other meteorological factors such as relative humidity and wind speed, both of which can affect water demands (Brentan et al., 2017; Zhou et al., 2002). Historical records for the daily air temperature and precipitation parameters from two weather stations (Blatchford and South Campus), which are both located in central Edmonton and are fairly close (7 km) to each other, were provided by Government of Canada (2019). Two stations were selected because severe weather conditions and maintenance processes often leads to gaps in meteorological observations – values from the South Campus station were used to fill blanks when the observations from Blatchford station were missing. Additionally, daily weather forecasting data were taken from a weather forecasting website (CustomWeather, 2019), which provides the weather prediction of the Blatchford area for the next 15 days.

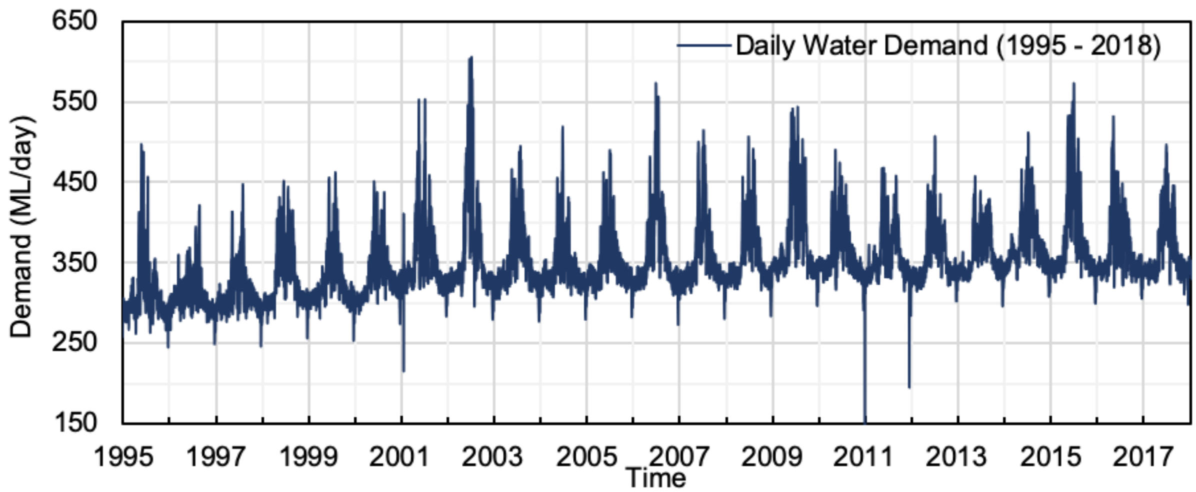


Fig. 3-5 Historical daily record for water demand from 1995 to 2018

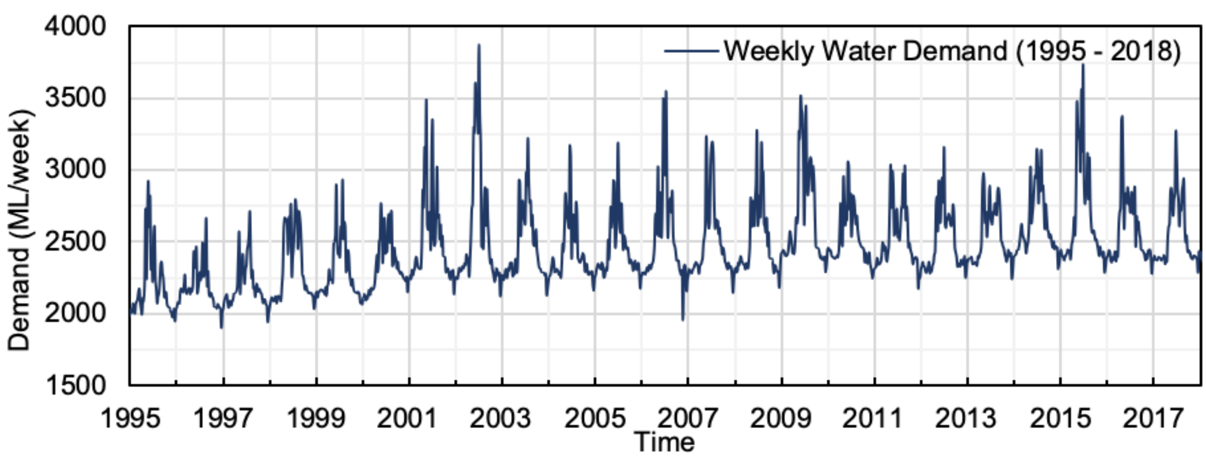


Fig. 3-6 Historical weekly record for water demand from 1995 to 2018

The major datasets used in the long-term study included water demand, water conservation, the historical weather record, global climate model outputs, and population:

- The historical weather record used in long-term forecasting, which was also prepared for ANN models, was the same as that used in the short-term forecasting, and included historical weekly maximum, minimum and average maximum air temperature (°C) and weekly total precipitation (mm).
- Long-term climate projections from 2019 to 2100 were obtained from three statistically downscaled daily Canada-wide climate scenarios, which are based on Global Climate Model (CanESM2) projections from the Coupled Model Intercomparison Project Phase 5 (Taylor et al., 2012). Pacific Climate Impacts Consortium climate scenario datasets include daily values of maximum and minimum temperature, and precipitation from 1950 to 2100 at 10 km resolution (PCIC, 2019).
- Population data came from a City of Edmonton growth study, which included population projections to 2066 under two growth scenarios (City of Edmonton, 2018). The complete population dataset was composed of this projection and the historical population data from the City of Edmonton.
- Historical records of EWSI's Edmonton region water service area's weekly municipal water demand for 1995 to 2018 were obtained from EWSI. Furthermore, historical records of annual water demand from 2000 to 2018 for multi-residential, residential, regional, ICI, and non-revenue use were derived from City of Edmonton (2019).
- Parameters to quantify the adoption status and the effect of water conservation policies were obtained from the original CWMM, which uses general data from a large North American

study (DeOreo et al., 2016) and makes assumptions for unavailable data, as described by (Wang & Davies, 2018).

Table 3-1 lists all the data used for the study, along with their sources.

Table 3-1 Data used in this study and data sources

	Data Type	Source	Period	Scale	Variables used
1	Historical weather record	Government of Canada (2019)	1995-2018	Daily	Minimum air temperature, maximum air temperature, precipitation
2	Global climate model outputs	PCIC (2019)	1995-2100	Daily	Minimum air temperature, maximum air temperature, precipitation
3	Historical population	EWSI	1995-2018	Annual	Population
4	Population projection	City of Edmonton Growth Study (2018)	2018-2066	Annual	Projected population growth rate
5	Historical municipal water demand	EWSI	1995-2018	Daily	Total municipal demand (Edmonton region water service area)
6	Historical water demand by end uses	City of Edmonton (2019)	2000-2018	Annual	End-use demand
7	Water conservation parameters	Wang & Davies (2018) DeOreo et al. (2016)	--	--	Water reduction from xeriscaping, low-flow appliances and greywater reuse; percentage houses with mentioned policies; change rate of policies; max adoption rate.

Chapter 4 Short-term Water Demand Forecasting Using ANNs

4.1 Introduction of Short-term Water Demand Forecasting

Short-term water demand forecasting plays a crucial role in urban water demand management, which could help water utilities set the operational schedule and make the allocation decisions beforehand (Herrera et al., 2010; Jain & Ormsbee, 2002). One important aim of forecasting is to ensure that water supply aligns with the demands of all the consumers in a city (Herrera et al., 2010). Traditionally, operators always supply water according to their experience or the previous day's water demand (Zhou et al., 2002). However, weather conditions such as temperature, pan evaporation, rainfall, wind speed, relative humidity, and precipitation could affect residents' water use behavior and bring significant uncertainty to demand estimations (Praskievicz & Chang, 2009). Therefore, accurate and reliable forecasts of short-term demand can help operators provide water in a more effective and efficient way.

Previously, conventional methods such as linear regression and time-series approach have been applied for water resources variable forecasting, especially the forecasts of water demand, in order to help operation and management (Adamowski et al., 2012). However, short-term water demand with seasonal variations mostly exhibits a nonlinear and nonstationary pattern, which typically leads to poor performance in traditional modeling (Adamowski & Karapataki, 2010; House-Peters & Chang, 2011; Pingale et al., 2014; Rathinasamy et al., 2013; Rathinasamy et al., 2014). To give the water operators and consumers a better understanding of the variable water demand, it is essential to extract the information included in the data. Artificial neural networks are an appropriate technique that could improve the efficiency and accuracy of the prediction.

This chapter focuses on fast, efficient approaches for short-term (1-day and 1-week lead time) urban water demand forecasts, aiming to achieve reliable daily and weekly predictions. .

4.2 Artificial Neural Networks

4.2.1 Basic Components

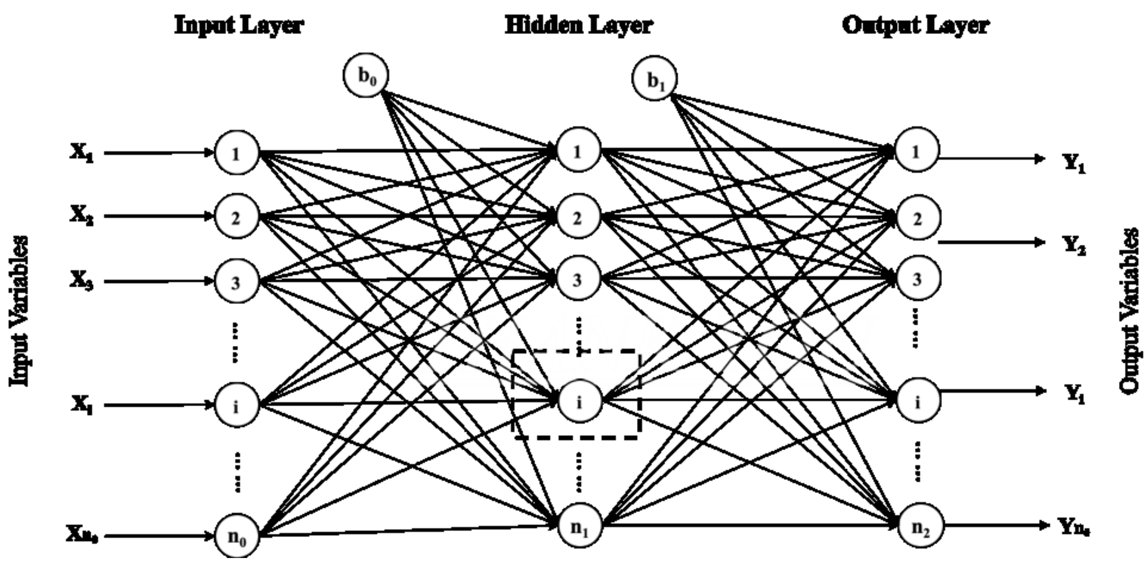
The origin of Artificial Neural Networks is in biology: ANNs are artificial computing systems that mimic the biological neural networks that constitute human brains. ANN "learns" and extracts patterns from given examples, without the requirement of specific learning rules. A typical architecture of an ANN is shown in Fig. 4-1(a) as an example.

The main component of an ANN is a group of connected computational processing units, which are called nodes or neurons, based on the analogue of biological neurons. Neurons are typically formed as multiple layers. Signals flow from the first layer (the input layer) to the last layer (the output layer), possibly passing multiple internal layers. Those internal layers that are not "visible" – processed signals move to other internal layers instead of being output as results – and are commonly called hidden layers; therefore, the neurons in hidden layers are therefore called hidden neurons.

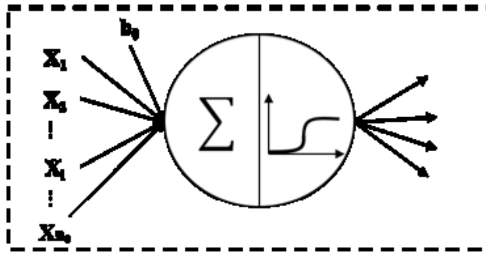
Signals passed by the neurons in an ANN take the form of numbers, rather than the electrical or chemical signals of biological neural networks. Neurons in one layer receive signals from the former layer, process the signal and then send it to the connected neurons in the next layer through the connections or "edges". Edges contain a "weight" that is adjusted through the learning process; this weight adjusts the contribution of the signal. Each "downstream" neuron receives and sums all data over its weighted contributing "upstream" connections. The summed values are next processed by activation functions and the produced results flow either to the next hidden layer or to the output layer as shown in Fig. 4-1 (b). Different layers can incorporate different activation functions. These activation functions are core processing components in an ANN which can define the outputs of neurons after the inputs are summed over weighted connections. They are functions applied to the weighted sum of the inputs and the bias as shown in the Equation (1), and their form is described in greater detail later in this chapter.

$$Y = f(wX + b) \tag{1}$$

where *Y* is the output value of a hidden neuron, X is the input value of a hidden neuron, *w* is the weight contained in the "upstream" connection, b is the bias, and the activation function is given by *f()*.



(a)



(b)

Fig. 4-1 Multilayer feed-forward ANN and processing element architectures

4.2.2 Network Structure

According to the flow direction of the signals, ANNs can be categorized as feedforward neural networks or recurrent neural networks. A feedforward neural network is the first and simplest type of artificial neural network invented (Schmidhuber, 2015). The term “feedforward" indicates the information is only transmitted forward in the network, rather than forming a loop. Layers only accept the information from the previous layer and its computational results exclusively contribute to the processing action in the subsequent layer. Such networks are relatively straightforward, and are extensively used in pattern recognition (Subramanian, 2014). They are ideally suited for modeling relationships between a set of input variables and output variables. In contrast, the connections between neurons of a recurrent neural network form a directed cyclic structure that allows a RNN to save the information from the mapping between the inputs and outputs at the current timestep and predict the output sequence at the next step (Salehinejad et al., 2017). This characteristic allows recurrent neural networks to achieve complex time series modeling such as speech recognition (Graves et al., 2009; Sak et al., 2014). However, they require large training datasets and long computational time since large numbers of weights and biases need to be trained as a result of the network’s structural complexity. In practice, researchers prefer feedforward models, which require less computational time, when facing problems that can be solved as well as through use of the recurrent models (Brink et al., 2016). In this study, to simulate the relationship between weather variables and water demand, the feedforward neural network is selected.

The simplest structure of ANN is the single-layer perceptron, which only contains the input and output layers and the inputs flow directly to the outputs. Multilayer perceptron consists of multiple layers of computational neurons, where each neuron directly connects to the neurons of the subsequent layer. The number of hidden layers in a feedforward network is flexible according to the complexity of the problem to be solved. Researchers have found that the best approach is to use one hidden layer and then change the number of neurons and/or training data sets until the best performance is achieved. Cybenko (1989) states that three-layer networks are adequate for simulating any arbitrary functions with no constraints on numbers of neurons and weights and without concern for optimization of the learning time. Freeman & Skapura (1991) argue that three layers are generally sufficient, although sometimes a problem is solved more easily in terms of the calculation time with more than one hidden layer. Thus, in this study, the three-layer architecture was selected for short-term water demand forecasting thinking of the calculation efficiency and the limited number of input variables.

The optimum number of hidden neurons also determines the structure and the size of an ANN. A small network with insufficient numbers of hidden neurons may fail to generalize well based on the training data. However, excessive numbers of hidden neurons tend to reproduce the whole training data by deriving exclusive equations for every set of inputs and output through a large number of weights, which may lead to prefect accuracy in the training process but bad performance in making predictions with new data – this is a problem typically called “model overfitting”. Further, optimizing weights is very time-consuming, which reduces the training efficiency. Some researchers have proposed rules of thumb to estimate the number of hidden neurons (Blum, 1992;

Boger & Guterman, 1997; Linoff & Berry, 2011); however, none of those rules can be applied under arbitrary circumstances without consideration of the sample size, the type of activation function, and the training algorithm (Xu & Chen, 2008). Therefore, although it takes quite a long time for processing, choosing the number of hidden neurons per layer remains an important and iterative process.

4.2.2 Learning Algorithm

(1) Backpropagation Training Algorithm

A standard and popular learning algorithm for ANNs is the backpropagation (BP) algorithm (Nawi et al., 2017). The BP training algorithm has been widely used because of its ease of use and excellent approximation ability for complex non-linear functions (Hammerstrom, 1993). The meaning learning process of the BP algorithm is accomplished by adjusting the weights in response to the error between the outputs predicted by the network (y_{sim}) and the actual outputs (y_{act}). The measure of error used is the “mean squared error” (E), which is calculated for the total n sets of predicted and actual outputs, as in Equation (2).

$$E = \frac{1}{n}\sum_{i=1}^{n}(y_{act} - y_{sim})^2 \qquad (2)$$

Where E is the mean squared error, y_{sim} is the outputs predicted by the network, y_{act} is the actual outputs, n is the number of the sets of predicted and actual outputs.

The generalized delta rule is used in the BP algorithm to reduce the error by altering the weights. In a backpropagation neural network (BPNN), the network is initialized with random weights. After the first computation with randomly-initiated weights, errors are produced in the output layer and are fed back through the connections, with adjustment of weights to minimize the error through a gradient descent calculation. The gradient is calculated as Equation (3) and the weight is adjusted as Equation (4). The whole optimization process repeats until a local minimum of the error function is found.

$$\nabla E = \left(\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial w_2}, \dots, \frac{\partial E}{\partial w_p}\right) \tag{3}$$

$$\Delta w_i = -\gamma \frac{\partial E}{\partial w_i} \quad \text{for } i = 1,2,3, \dots, p \tag{4}$$

In equations (3) and (4), w is the weight, p is the total number of weights, and γ represents a learning constant defining the step length of each iteration step along the negative gradient direction.

(2) Extreme Learning Machine

An Extreme Learning Machine (ELM) is a least square-based single-hidden layer feedforward neural network that applies a special algorithm invented by Guang-Bing Huang (Brink et al., 2016; Huang et al., 2004). In an ELM, the input weights and biases of hidden neurons are set randomly and are not altered in the learning process. However, the output weights of hidden neurons are optimized, using the least-squares solution to minimize the error. (Huang et al., 2004) provide a detailed introduction to the mathematical background. Unlike the backpropagation algorithm, only the output weights of hidden neurons in ELM need to be determined by iterative calculation for the optimal learning performance. Furthermore, in most cases, optimization of output weights of hidden neurons is complete after one step. Therefore, ELMs can be trained significantly faster than networks trained with the backpropagation algorithm (Yu et al., 2016). Additionally, the fast learning speed does not lead to a decrease in accuracy, and the accuracy of ELMs is slightly better than BPNNs in some cases (Song & Liò, 2010; Zou et al., 2017).

4.4 Model Development

This study explores the performance of ANNs for daily and weekly water demand forecasting and compares two types of ANNs (ELM and BPNN) with a conventional approach, Multiple Linear Regression (MLR) that has commonly been used to predict water demand. Hundreds of experiments on ANN configuration were conducted to determine the optimal approach for daily and weekly simulation. The specific issues addressed included, 1) the applicability of ANNs to water demand forecasting with meteorological variables and 2) the approaches best used to identify the appropriate structure for the ANN (e.g. the number of layers and the number of hidden nodes). Practical outputs included a user-friendly application based on the optimum daily and weekly ANN models, which was tested for operational use by EWSI from April to December 2019.

All models – MLR, BP neural network model and ELM – were developed in the R programming language (R Core Team, 2019). R is a free and open-source language that includes a collection of powerful tools and libraries and offers complete and applicable packages for forecasting techniques, including the conventional models and ANNs. As introduced in Section 4.2, the architecture of neural networks is limited by many parameters that can be altered based on the problem to be solved. To determine the relationship between the weather pattern and the water demand, feedforward networks with single hidden layers were selected to test our two training algorithms: ELM and BP. For the generation of the ANN models, it is necessary to determine the following parameters: 1) the number of input neurons, 2) the number of layers, 3) the number of output vectors, and 4) the number of hidden neurons. The issues addressed include the selection of better-correlated input, transfer functions, and the optimum number of hidden neurons. The first step of ANN model development is configuration to fit the data by setting initial numbers of input and output neurons.

Water demand forecast modeling typically involves a number of variables that function as inputs. For daily water demand forecasting, weather conditions such as temperature and precipitation as well as the water demand of the previous two days are often assumed to have a significant influence on today's water demand. However, with potentially frequent and severe summer thunderstorms in Edmonton, precipitation may appear over more than two consecutive days, with a different influence on water demand than the assumed importance of 2 prior days of precipitation. Thus, the effective period of precipitation was assumed to extend up to 5 days. The (binary) occurrence of precipitation was also incorporated, since previous studies in Canada found it to be a better predictor than the amount of precipitation in short-term forecasting (Adamowski & Karapataki, 2010; Jain et al., 2001).

In addition to meteorological data, water demand is also known to vary with the day of the week and day of the month. Therefore, to better explore the periodicity of water demand, indices were used in models (i.e. *"day-in-week"*, *"day-in-month"*) to investigate their effect on model performance as compared with those models without such indices. For instance, Dec 19th, 2019 is the third day in a week and the nineteenth day in a month, so two indexes of Dec 19th are 3 and 19 respectively. The total number of potential inputs tested in this study is 25 as shown in Table 4-1. Similarly, 17 potential inputs shown in Table 4-2 were examined for weekly forecasting.

Table 4-1 Potential input variables for daily forecasting

Time	D [b]	T_{max} [c]	T_{min}	T_{mean}	AP [d]	OP	"*day in week*"	"*day in month*"
d [a]		√	√	√	√	√	√	√
d-1	√	√	√	√	√	√		
d-2	√	√	√	√	√	√		
d-3					√	√		
d-4					√	√		
d-5					√	√		

[a] *d* is the day to be predicted, *d-1* is the day before the day to be predicted, …, and *d-5* is five days before the day to be predicted,

[b] *D* is the daily water demand,

[c] T_{max} is the daily maximum temperature, T_{min} is the daily minimum temperature, T_{mean} is the daily mean temperature,

[d] *AP* is the amount of precipitation in a day, *OP* is the occurrence of precipitation in a day (0 means no precipitation; 1 means precipitation occurs).

Table 4-2 Potential input variables for weekly forecasting

Time	D [b]	T_{max} [c]	T_{min}	T_{mean}	AP [d]	OP
w [a]		√	√	√	√	√
w-1	√	√	√	√	√	√
w-2	√	√	√	√	√	√

[a] *w* is the week to be predicted, *w-1* is the week before the week to be predicted, and *w-2* is two weeks before the week to be predicted,

[b] *D* is the weekly water demand,

[c] T_{max} is the weekly maximum temperature, T_{min} is the weekly minimum temperature, T_{mean} is the weekly mean temperature,

[d] *AP* is the amount of precipitation in a week, *OP* is the occurrence of precipitation in a week (0 means no precipitation; 1 means precipitation appears).

The number of inputs used in the network will govern how many neurons are required in the input layer, so it is important to determine the optimal input combination that is most relevant to the water demand. A selection process helps to remove unimportant input variables so that only the most important predictors are used in model development (Hammerstrom, 1993), which simplifies the model, reduces the training time and increases the generalization ability of the model (James, Witten, Hastie, & Tibshirani, 2013). Two approaches are applied for input selection. The selection process first screens raw data by the strength of the input-output correlation, which indicates whether a variable should be included in the input. A strong correlation between two input variables, for example, implies that one of them is redundant. As the total number of inputs is limited, the "trial and error" method was then based on the result from correlation examination to determine the most important variables in water demand forecasting. Any addition or removal of variables in trial-and-error approach aimed to get a better result. In this way, hundreds of possible input combinations were tested through the ANN and the performance was compared.

Before introducing data for the selected variables into the ANN, the data were normalized. Normalization decreases the variance of the inputs and compresses all inputs into the same range, so that every input influences the result to the same level. For example, temperatures vary from approximately -10 to 40 °C while precipitation has a totally different range of 0 to 100 mm, which may cause precipitation to affect the output more because of its larger value. Therefore, the whole dataset with all the weather variables was normalized between [-1, 1], using Equation (5).

Additionally, the dataset was partitioned into training and testing sets, with the size of the training data set to a typical number of 70%. Thus, 70% of the data were used to train the model and the remaining 30% were used to test the generalization of the trained model. During the training process, the neuron weight values were adjusted repeatedly with every pair of input and output, based on the predetermined learning algorithm. The training process stopped when the preselected Mean Squares Error (MSE) value was reached.

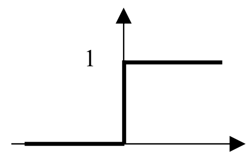
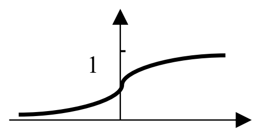
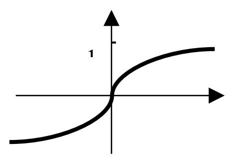
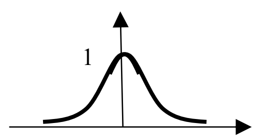
$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{5}$$

Where x' is the normalized value, x is an original value, x_{min} is minimum value in the whole dataset, x_{max} is the maximum value in the whole dataset.

The next step was to optimize the network. The main purpose of this optimizing process was to find a network with the appropriate size – one large enough to abstract the problem but small enough to generalize well or produce the desired output from the provided input (Hammerstrom, 1993). After the number of inputs and output was determined, the number of hidden neurons was manipulated, with their value determining the size of the ANN. No rules are applicable for the optimization, and so the process began with the simplest configurations and an assessment of their acceptability. If they were not acceptable, more sophisticated configurations were proposed. Within a pre-set threshold from 1 to 100, the optimum number of hidden neurons was determined as the number of neurons that presented the lowest generalization error or MSE through a trial-and-error approach. MSE was calculated each time the number of hidden neurons was changed and the ANN with the minimum error was selected as the optimal ANN.

Except for optimizing the number of hidden neurons, four common types of activation functions – Binary step, Logistic (Sigmoid), TanH, and Gaussian – were tested to give the optimal performance (see Table 4-3).

Table 4-3 Activation functions (Hara & Nakayama, 1994; Özkan & Erbek, 2003)

Name	Plot	Equation
Binary step		$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$
Logistic (Sigmoid)		$f(x) = \dfrac{1}{1 + e^{-x}}$
TanH		$f(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$
Gaussian		$f(x) = e^{-x^2}$

4.5 Model Validation

Cross validation was used to evaluate models developed from multiple subsets of the dataset, which helps give a more accurate indication of how well the model generalizes to unseen data. In this thesis, ten different sets of training data (70%) and testing data (30%) were randomly selected and input to the ANN model sequentially – in other words, there were ten repetitions of model development. The average value of mean absolute error (MAE) yielded from these ten repetitions was calculated. The model that produced the minimum average MAE was selected as the optimum model with the greatest generalization ability.

The model was finalized by applying the chosen model for the whole dataset. In addition to the MAE, the coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (NRMSE) were also calculated and used to present the prediction performance. Note that the final model was also tested by EWSI through a comparison of projected values against actual demands from April to December in 2019. Its performance was evaluated using percentage errors (PE) and the associated statistical indicators such as the maximum PE, minimum PE, mean PE and standard deviation of PE.

(1) Coefficient of determination (R^2)

R^2 provides a measure of how well the observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model (Barrett, 1974). The closer R^2 is to 1, the better the model performs. R^2 is given as,

$$R^2 = \frac{\mathrm{n}(\sum y_{obs} y_{sim}) - (\sum y_{obs})(\sum y_{sim})}{\sqrt{[n\sum {y_{obs}}^2 - (\sum y_{obs})^2][n\sum {y_{sim}}^2 - (\sum y_{sim})^2]}} \quad (6)$$

Where y_{sim} represents the simulated value produced by ANN model, y_{obs} is the observed value and n is the number of total data points in calculation.

(2) Mean Absolute Error (MAE)

The absolute error is the absolute value of the difference between the forecasted values and the observed values. MAE tells how large an error in the forecast is expected to be on average (Chai & Draxler, 2014). It is given by,

$$MAE = \frac{1}{n}\sum |y_{sim} - y_{obs}| \quad (7)$$

(3) Root Mean Square Error (RMSE)

The RMSE describes how concentrated the data is around the line of best fit – lower RMSE values indicate less residual variance (Chai & Draxler, 2014). RMSE is a measure of accuracy used to compare simulation errors of different models for a particular dataset, but cannot be applied to compare results for different datasets, since it is scale-dependent (Hyndman & Koehler, 2006). It is given by,

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (y_{sim} - y_{obs})^2} \tag{8}$$

(4) Normalized Root Mean Square Error (NRMSE)

To compare the performance of the ANN model with other models using different scales, NRMSE is used. NRMSE is calculated by the following formula,

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\bar{y}_{obs}} \tag{9}$$

(5) Percentage Error (PE)

The PE is calculated as the differences between observations and the forecasts, divided by observations (Bodt, 1998). It is given as,

$$\mathrm{PE} = \frac{y_{sim} - y_{obs}}{y_{obs}} \tag{10}$$

(6) Standard Deviation of Percentage Error (SDPE)

Finally, the standard deviation of the percentage error is a measure of error variations, calculated as the square root of error variance by determining the variation between each data point relative to the mean value. The equation is,

$$\mathrm{SDE} = \sqrt{\frac{1}{n}\sum (\mathrm{PE} - \overline{\mathrm{PE}})^2} \tag{11}$$

4.6 Model Application

A user interface was developed for the demand forecasting for use by EWSI. This interface permitted water professionals to apply well-trained models for daily or weekly water demand forecasting. In this thesis, the "Shiny" user interface package for the R language (R Core Team, 2019) was applied to produce an interactive web app.

A "shiny" application is supported by three components: the user interface (ui), the server and the global environment, all of which are developed in different coding files. The file called "ui. R" describes the layout of the web-based interface such as the position of buttons and sliders. The "server. R" file develops a real-time connection between users' inputs in the app and the corresponding results. Finally, the global environment records all the default information such as the parameters of the ANN.

The resulting "shiny" application allowed users to achieve predictions in two different ways. Users could rely on weather data automatically retrieved from a weather forecasting website every day (Fig. 4-2) or they could input the values manually (Fig. 4-3). For automatic retrieval, it was essential to find a reliable and continuous source of the predicted inputs to support the forecasting process. The weather forecasts on the *CustomWeather* website and the historical records on the Government of Canada website are updated daily, with few missing values. To extract the weather forecast data, an R library – "XML2" – was used in this study. It was possible to obtain the information contained in the URL by utilizing the read_html and html_nodes function. Then through pre-processing, the retrieved data were made to match the format of the original inputs and were input to an optimal trained ANN model, along with manually-input water demands of previous days, to produce the water demand predictions. Weekly forecasting requires similar procedures. The first function depending on automatically-retrieved weather data is developed for daily/weekly prediction and the recheck of the recent values. The second function that requires manually-input values allows users without any prior knowledge to experiment with the ANNs. Water professionals can easily examine the water demand under arbitrary weather conditions, which may help water utilities prepare also for extreme weather events.

4.7 Summary

This Chapter first gave a detailed introduction to ANNs, including the components, structure and learning algorithms. Then the development procedures of ANNs for daily and weekly water demand forecasting were described. The inspections implemented to obtain the optimum model included the optimum number of inputs and hidden neurons, and the appropriate activation function. The relative importance of the factors that affect the Edmonton region's water demand were analyzed by testing hundreds of input combinations. The rest of this chapter discussed the validation approach and the developed user interface, which was tested by EWSI. Model analysis and the testing results are described in Chapter 6.

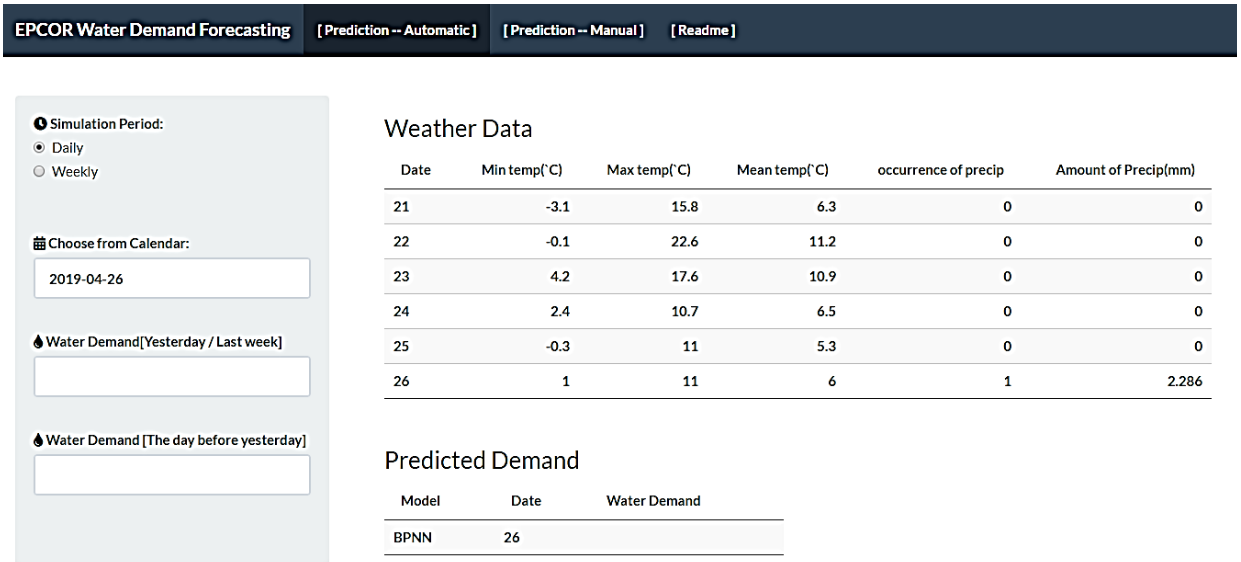


Fig. 4-2 Interface with scrapped weather data

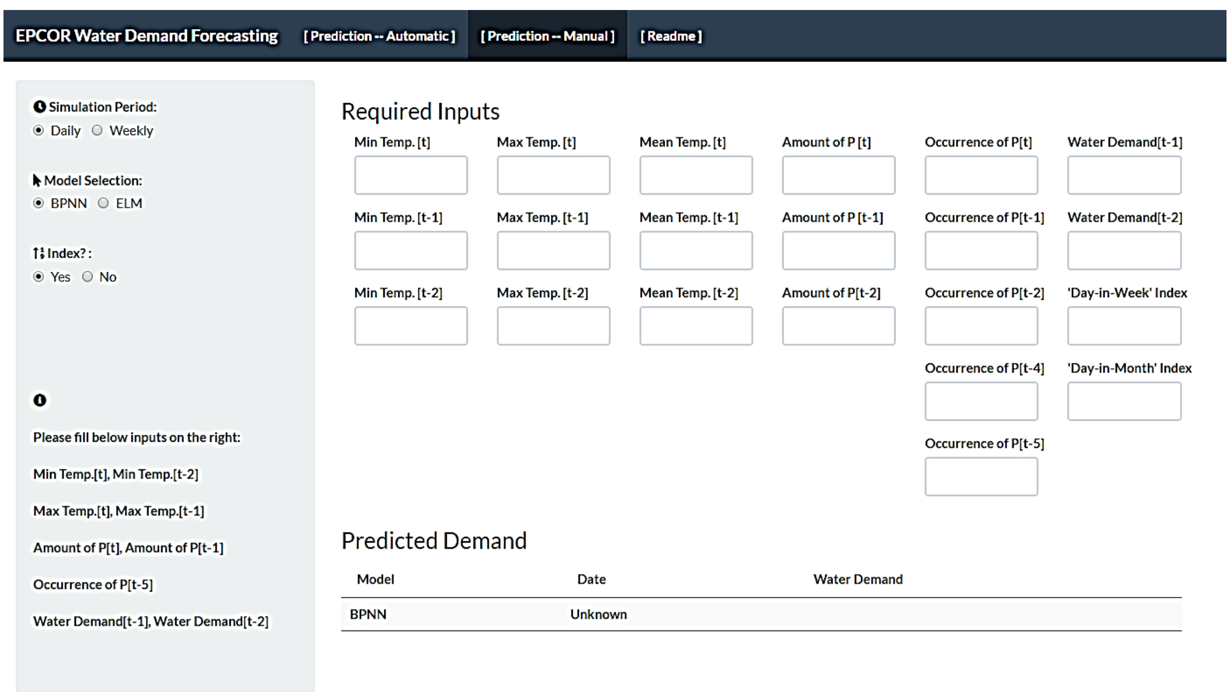


Fig. 4-3 Interface with manual inputs

Chapter 5 Long-term Forecasting Using Hybrid Models[1]

5.1 Introduction of Long-term Water Demand Forecasting

The world's population is growing by about 80 million people per year (USCB, 2019) and is predicted to reach 9.5 billion by 2050. The population living in municipal areas is an important component of the total world population. On average, the population served by municipal water supply in 2018 is 81% in high-income countries, 53% in middle-income counties and 33% in low-income countries (the World Bank, 2018). In addition to population growth, climate change is also becoming a common concern for water management modeling. Nearly all regions of the world are expected to experience the impact of climate change on water resources and freshwater ecosystems (IPCC, 2014). Climate change challenges existing water resources management practices by increasing uncertainties related to both water supply and demand.

Under the potential combined impact of climate change and population growth, sustainable water management is required to align the available supplies with future demand. In most urban systems of North America, the total municipal water demand increases with population growth, while a declining trend of per capita water use has been found over the past decades due to water conservation efforts. These efforts are expected to have long-term impacts and new conservation policies may be adopted with the development in the future. Therefore, changes in water demand are expected in the future as a result of several factors including climate change, increasing population, and water management efforts (Arnell & Liu, 2001). The majority of the relevant research has focused on potential changes in only one or two drivers of change in municipal water management (Ahmad & Prashar, 2010; Amisigo et al., 2015; Parkinson et al., 2016; Rasoulkhani

[1] Liu, H., Xing, R., Davies, E.G.R., "An analysis of the relative importance of municipal water demand drivers using a hybrid model". To be submitted to Science of the Total Environment.

et al., 2018; Stavenhagen et al., 2018; Wang et al., 2018). As limited research has focused on long-term municipal water management, a comprehensive model can significantly enhance the potential for adaption to future changes and is therefore crucial for decision making in water management. SD models, as introduced in Chapter 2, are an approriate tool for long-term projection, since they can separate total municipal water demand into specific end uses and simulate targeted water saving policies for each end use. However, SD models rely on assumptions which may decrease their simulation accuracy. In contrast, data-driven models such as ANNs and regression models can be very accurate, they extract a constant pattern based on current conditions. In this study, a hybrid model was developed that consists of a SD model, an ANN and regression models. Results from data-driven models are regarded as base values and are further adjusted by other variables related to future policy changes in SD model. The novelty of this approach lies in its end-use based framework, which can distinguish future changes in individual water uses, and the application of appropriate simulation approaches selected for specific end uses, which can sufficiently take advantage of the applied models and remedy their weakness. The developed water demand simulator may help water professionals develop more sustainable water management practices to meet growing demands under changing conditions, and improve understanding of the relative importance of water demand drivers on future water demands in the study area.

5.2 Model Introduction

This section introduces the model components and provides the rationale for their integration. A more detailed description of each model component is in section 5.3. The Edmonton Water Demand Simulator (EWDS) is modified from the Calgary Water Management Model (CWMM), a comprehensive tool for long-term water management that simulates weekly per capita, sectoral (end use) and total municipal water demands to 2040. The CWMM can simulate effects of potential changes in socio-economic conditions, water conservation facilities and policies, and reveal the combined effect of these changes on water demands. A detailed description of the structure and capabilities of the CWMM can be found in (Wang & Davies, 2018).

The simulation performance of CWMM is generally less accurate than data-driven simulation approaches (Adamowski & Karapataki, 2010; Velo-Suárez & Gutiérrez-Estrada, 2007). The simulation performance of CWMM for the 2005-2015 period is indicated by R^2 of 0.76 and Root Mean Square Error (RMSE) of 190ML, while the average weekly demand is around 3300 ML. The most seasonally-variable component – outdoor water demand – is calculated from a set of climate-based empirical relationships developed for Calgary through local weekly temperature and rainfall (Akuoko-Asibey et al., 1993; Chen et al., 2006) in CWMM. However, those equations do not produce accurate simulations and cannot be applied easily to other municipal areas. Therefore, the EWDS retains many components of the CWMM and has the same spatial and temporal resolution, but replaces its residential outdoor water demand model and its simple method for climate change projections (which use data modified from historical records) with a more accurate ANN model that uses climate inputs from global climate scenarios simulated with GCMs (PCIC, 2019) to project outdoor demands into the more distant future .

Using EWSI data, the EWDS also replaces assumed constant ICI values in the CWMM with a regression model and disaggregates the original total residential demands into multi-residential (regression model) and household-metered residential (SD) components. Finally, the EWDS adds a regional model that mirrors the structure of the municipal model to represent the regional wholesale water market. The addition of the regional and multi-residential components and revisions of the outdoor and ICI demands adds greater flexibility to the model, improves its replication of historical demands, and permits its application to other communities. The structure of the EWDS is shown in Fig. 5-1, where end uses in light gray are new additions to the EWDS and end uses in dark grey are modified from the CWMM.

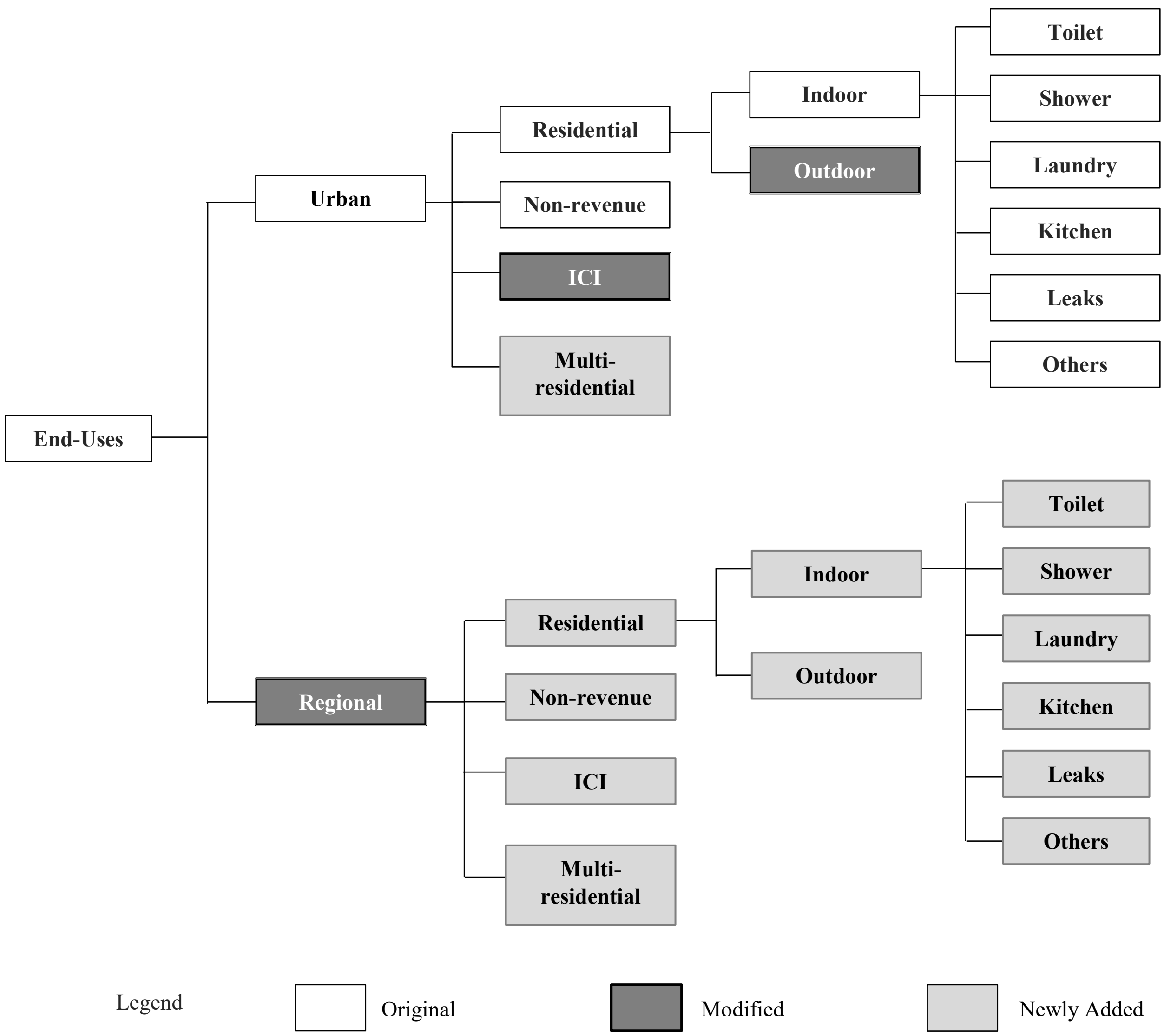


Fig. 5-1 End-use framework of the modified model

5.3 Model Development

The EWDS divides municipal and regional water demand into 20 end-use categories (Fig. 5-1) based on recommendations from EWSI, DeOreo et al. (2016) and Mayer et al. (1999). These categories include toilet, shower and bath, laundry, kitchen (water used for faucets and dishwashers), leaks (unexpected losses of residential water from the household plumbing system for no beneficial purpose, such as toilet flappers and faucet drips), other, outdoor, ICI (Industrial, Commercial, and Institutional), multi-residential (water used for buildings where more than four separate dwelling units are metered by a single water meter and are primarily used for domestic purposes) and non-revenue uses (water used for firefighting and distribution main flushing, and lost through system main breaks and leakage).

The EWDS calculates the total water demand from equation (1).

$$WD_{total} = WD_{res,urb} + WD_{multi-res,urb} + WD_{ici,urb} + WD_{non-rev,urb} + WD_{reg} \tag{12}$$

Where WD is water demand (in ML), and the subscripts are *urb* for urban use, *reg* for regional use, *res* for residential use, *multi-res* for multi-residential use, *ici* for ICI uses, and *non-rev* for non-revenue uses.

5.3.1 Residential Water Demand

Residential use is simulated with equation (2), which separates indoor and outdoor uses,

$$WD_{res,urb} = \left(PCWD_{indoor,urb} + PCWD_{outdoor,urb}\right) * POP_{urb} \tag{13}$$

$$PCWD_{indoor,urb} = \sum\left[BPCWD_{k,urb} * f_k(policy)\right] \tag{14}$$

$$PCWD_{outdoor,urb} = BPCWD_{outdoor,urb} * f_{outdoor}(policy) \quad (15)$$

$$= f_{ANN}(climate) * f_{outdoor}(policy)$$

Where PCWD is the per capita water demand (L/person/week); POP_{urb} is the municipal population (person); BPCWD is the base per capita water demand (L/person/week), which is a parameter that omits the effects of conservation policies or technologies; k represents the six indoor end uses – toilet, laundry, shower, kitchen, leaks, others; f_k and $f_{outdoor}$ are demand modifiers that represent the effects of conservation policies or technologies on the water demands from each indoor or outdoor water end use and f_{ANN} is the output of the new residential outdoor water demand ANN model (L/person/week).

(1) Indoor Water Demand

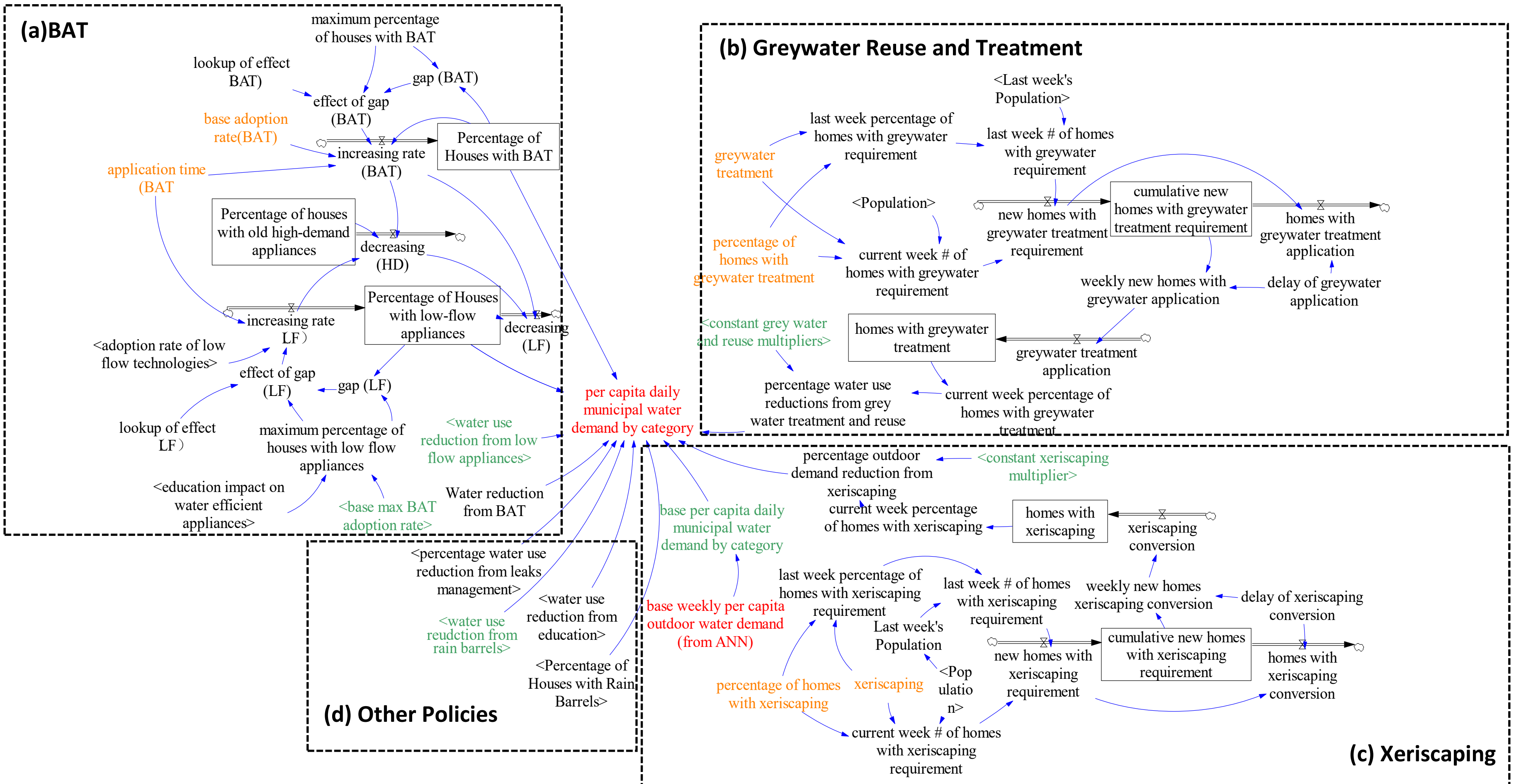
The per capita daily water demand of each indoor end use is determined by the base per capita demand and the fraction of households equipped with water conserving fixtures and appliances. Values for base per capita indoor demand by end uses are adopted from DeOreo (2016). Fig. 5-2 shows a screen capture of a number of variables required for simulation of the per capita water demand and the adoption of three policies used in the scenarios below, including a "best available technology" (BAT), greywater reuse and treatment, and xeriscaping in (a), (b) and (c). The BAT represents a general, non-specific fixture or appliance that is used to represent a high-efficiency water-conserving technology for a specific end use. A BAT is assumed to (significantly) exceed the performance of current technologies that are widely in use, and is assumed to be reasonably accessible to water managers in terms of its cost and advantages (Smith, 2002). Grey water reuse and treatment reduces indoor water demands by collecting wastewater from residential end uses such as showers, sinks, and washing machines and reusing the wastewater for toilet flushing, outdoor watering or even potentially laundry or shower (Vuppaladadiyam et al., 2019). Greywater and the BAT both reduce toilet demand and multi-residential demand in this study. Additionally, xeriscaping can reduce outdoor demand by replacing more common, water-intensive garden plants and turf with drought-tolerant plants (Fan, McCann, & Qin, 2017). Additional policies in (d) include rain barrels, leaks management, and education, which can be altered in EWDS but were not the focus of this study.

Stocks, shown as boxes in Fig. 5-2, can accumulate matter or information from the connected flows over time, while arrows connected with stocks and variables in an SD model represent transfer of information important for mathematical equations (Wang & Davies, 2018). The fractions of households with water-saving appliances are represented as stocks in EWDS, and their values increase with a changing adoption rate, which can be affected by unmet water demand or by policies that influence how widely implemented a low-flow fixture or appliance is. For example, in the case of the BAT, the adoption rate is slow at the beginning, increases to a maximum value at the middle of growth period, and then gradually decreases to zero as the prevalence of the BAT reaches its maximum value (typically 90%) – these dynamics cause the BAT prevalence to follow a logistical, or S-shaped, growth curve over time.

The per capita demand can then be calculated from the fractions of houses with and without water-saving appliances, the base per capita water demand for each end use, the number of end uses per day, and the water reduction from each low-flow appliance. As an example, per capita toilet water use would be calculated as the amount of water per flush for standard and low-flow fixtures multiplied by the percentage of households with each type of fixture multiplied by the number of flushes per person per day. Equation (16) is a more specific version of equation (13) for calculating per capita residential water demand.

$$PCWD = \sum_i \left\{ \left[\left(f_{lf,i}(1 - r_{lf,i}) + (1 - r_{lf,i}) \right) \right] * BPCWD_i - R_{gw,i} - R_{xr,i} \right\} \quad (16)$$

where i represents the residential water end uses, *lf* is low-flow appliances of fixtures including high-efficiency low-flow toilets, showers, washing machines, BAT, and so on, *gw* is greywater reuse and treatment, $f_{lf,i}$ are the percentages of households with low-flow fixtures, $r_{lf,i}$ are the fractional reductions of residential water demand (dimensionless), $R_{gw,i}$ is the water reduction from the grey water treatment policy (L/capita/day), and $R_{xr,i}$ is the water reduction from the xeriscaping policy (L/capita/day). Note that conservation policies specifically target individual residential end uses. For instance, xeriscaping only reduces the outdoor water demand, which means i only represents outdoor use since xeriscaping only affects outdoor water demand, and $R_{xr,i}$ will be non-zero where xeriscaping is implemented.



(Note: black: model variables, green: constants, orange: changeable inputs, < >: "shadow variables" that duplicated from other parts of the model)

Fig. 5-2 Simulation of per capita daily water demand

(2) Outdoor Water Demand

The base outdoor demand differs from indoor demands, since the weather variables such as temperature and precipitation affect it. During the winter season, the EWDS sets residential outdoor water demands to zero. In the summer season, the EWDS uses values from the ANN model described below. Because the starting and ending dates of winter depend on weather conditions and therefore differ each year, the EWDS determines whether to use the ANN model results from the input temperatures. Specifically, when the minimum temperature is below zero for two consecutive weeks in the autumn, the second week is considered to be the start of the winter season. Similarly, when the minimum temperature is above zero for two consecutive weeks in the spring, the second week is set to be the end of the winter season. This approach to separating the winter and summer periods was designed to be flexible in order to represent changes in outdoor water use timing with climate change to 2100.

The new ANN model for residential outdoor demand was developed according to procedures described in Chapter 4 and in Adamowski & Karapataki (2010)and required determination of, 1) the number of input vectors, 2) the number of layers, 3) the number of output vectors, and iv) the number of neurons. As described in Chapter 4, ANN development also required the selection of better-correlated input variables, appropriate learning algorithms and transfer functions, and the optimum number of hidden neurons. A three-layer feedforward neural network, one of the most straightforward and commonly used structures (Gagliardi et al., 2017), was also used here and was trained with the backpropagation learning algorithm. Input variables included the total water demand (*WD*) from the previous week and the weekly maximum, minimum, and mean temperatures (T_{max}, T_{min}, T_{mean}) and total precipitation (*P*) for the current and previous week. Because the ANN was developed for integration into the SD model, its size was minimized, restricting the number of hidden neurons. In optimizing model parameter values, the simplest configurations were tested first to determine their acceptability, with more sophisticated configurations subsequently tested. From a pre-set threshold of 1-30, the optimum number of hidden neurons was found to be 7 through a trial-and-error approach that minimized the Mean Absolute Error (MAE) and the sigmoid function was selected as the transfer function through a comparison of five alternative functions.

After training and optimization in the R programming language (R Core Team, 2019; see Fig. 5-3), the optimal ANN was determined, and reproduced in Vensim (Ventana Systems, 2019), the system dynamics software (see Fig. 5-4). Model performance is described in Chapter 6. Variables in the SD model were used to represent neurons and the coefficient matrix from the R workspace was combined manually with the SD variables to produce the necessary mathematical equations. Simulated values in the two models matched to within 99.99%. Further, the potential effect of water-saving policies should be considered in long-term forecasting. Therefore, the per capita outdoor water demand produced by ANN is adjusted by a xeriscaping multiplier, which represents the per capita water reduction from xeriscaping, in the SD model. More values such as the percentage of houses with xeriscaping, the adoption rate of xeriscaping and the maximum percentage of houses that will implement xeriscaping are used for calculating the total outdoor demand in the Edmonton region water service area.

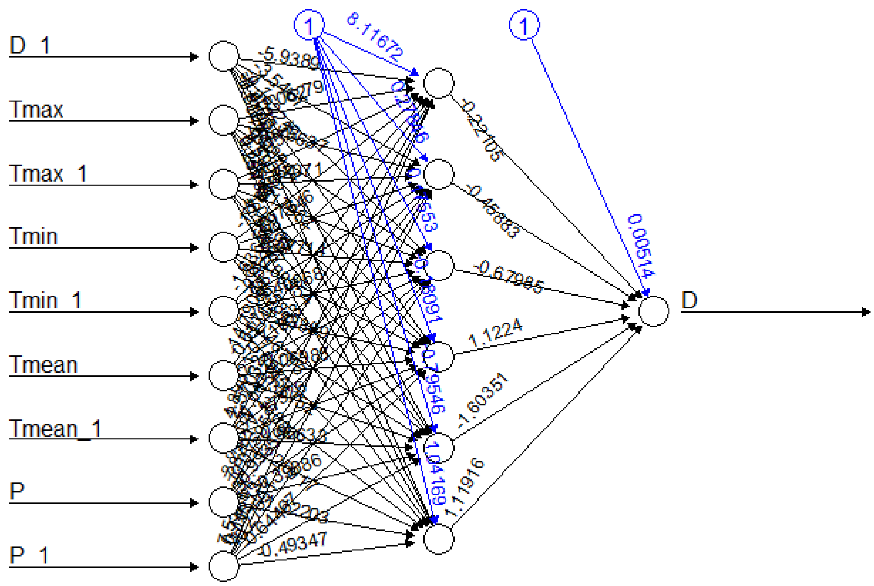


Fig. 5-3 ANN structure in R program

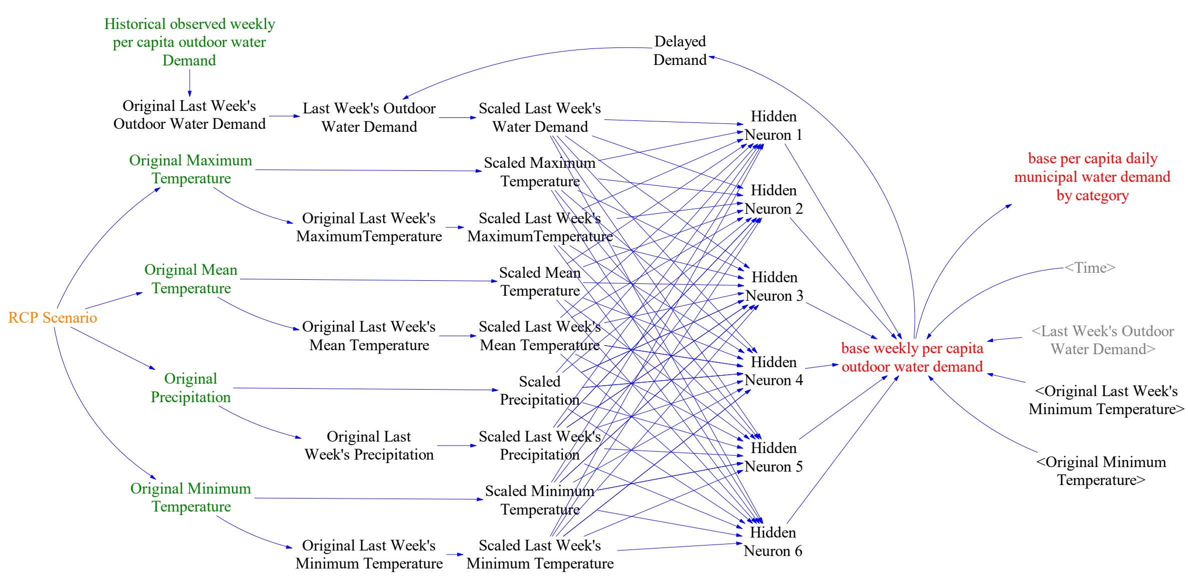


Fig. 5-4 ANN structure in Vensim

5.3.2 ICI and Multi-residential Water Demand

Water utilities measure ICI and multi-residential water consumption as the metered service at locations such as businesses, universities, institutions, and apartment buildings. For the EWDS, linear relationships were first developed to represent the connection between the municipal population and numbers of ICI (g_{ici}) or multi-residential ($g_{multi-res}$) services – see Fig. 5-5. Then, combining these two models with a per-service value in the system dynamics model permitted representation of the effects of water conservation policies. See equation (17) for the ICI model and equation (18) for the multi-residential model, where *PSWD* is the per-service water demand (L/metered service/week) and *SRV* is the number of service locations (metered service).

$$
\begin{aligned}
WD_{ici,urb} \\
&= PSWD_{ici,urb} * SRV_{ici,urb} \\
&= \left[BPCWD_{ici,urb} * f_{ici}(policy)\right] * g_{ici}(POP_{urb})
\end{aligned}
\tag{17}
$$

$$
\begin{aligned}
WD_{multi-res,urb} \\
&= PSWD_{multi-res,urb} * SRV_{multi-res,urb} \\
&= \left[BPCWD_{multi-res,urb} * f_{multi-res}(policy)\right] * g_{multi-res}(POP_{urb})
\end{aligned}
\tag{18}
$$

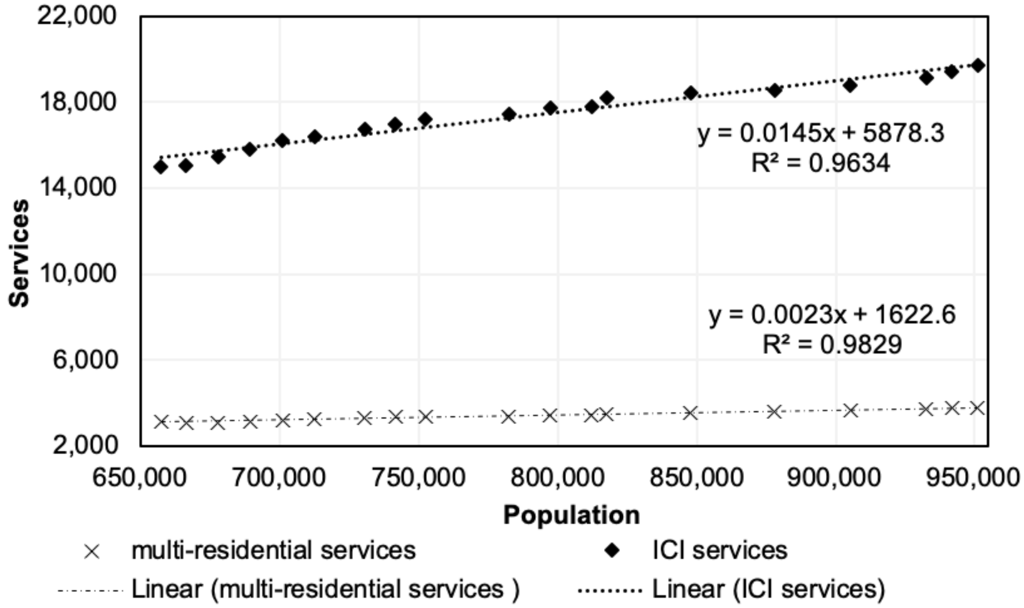


Fig. 5-5 Linear relationship between population and services

5.3.3 Regional Water Demand

Although Calgary provides municipal water only to a small regional market (4% of the total demand), EWSI sells a significant percentage of its total water production to communities outside Edmonton (Fig. 3-3). Therefore, to permit more detailed regional water demand projections, a broader representation of future demand scenarios, and wider applicability to other communities, a regional component was added to the EWDS. The regional component mirrors the structure of the urban component. Most parameters for the regional components are the same as for the urban components, such as the water reductions from water conservation policies and the maximum policy adoption level. However, initial conditions for water consumption and policy implementation in the Regional Service Area may differ from those within Edmonton, and so those values were altered slightly in the calibration process. Equation (19) calculates the regional water demand and forms an input to equation (12).

$$WD_{reg} = WD_{res,reg} + WD_{multi-res,reg} + WD_{ici,reg} + WD_{non-rev,reg} \quad (19)$$

5.4 Scenario Configuration

Scenarios help decision makers to explore possibilities, anticipate changes, and prepare coping strategies. In this study, they are designed to assess both relative and absolute effects of long-term changes in population, climate, technologies, and policies on water demands to 2100, and to engage water professionals and policymakers in terms of the broad policy choices that could be used to influence water use behaviors.

Three sets of demand drivers are considered in the scenario settings: climate, population, and water conservation efforts. These drivers are then combined to create sets of scenarios whose results can be compared to explore the effects of individual differences in drivers (low versus high degrees of change in a driver) or combinations of drivers (low changes in all three drivers versus high changes in all three, for example).

For the climate drivers, three Representative Concentration Pathways (RCPs) are used to represent the effects of different hypothesized atmospheric greenhouse gas concentrations (van Vuuren et al., 2011). RCP 8.5 represents the most severe global warming conditions, where CO_2 emissions continue to rise throughout the 21st century; under RCP 4.5 and RCP 2.6, CO_2 emissions peak in around 2040 and 2020 respectively and then decline substantially thereafter (Thomson et al., 2011; van Vuuren et al., 2011; Westervelt et al., 2015). The climate inputs to the EWDS include weekly maximum, minimum, and mean temperatures and the weekly total precipitation. To illustrate the potential effects of climate change in the Edmonton region, Fig. 5-6 compares weekly maximum temperatures for the last 5 years of the simulated period (2091-2100) under the three climate scenarios with observations for 5 recent years (2010-2019). On average, annual temperatures under

RCPs 2.6, 4.5, and 8.5 in the last ten years of the 21st century are respectively 1.9, 3.4, and 6.4°C (or 39%, 70% and 132%) greater than current annual average temperature of 4.8°C, the durations of sub-zero temperatures are approximately 4, 4, and 7 weeks shorter, and weekly precipitation amounts are 9.89, 10.43, and 10.45 mm, as compared with 7.24 mm currently.

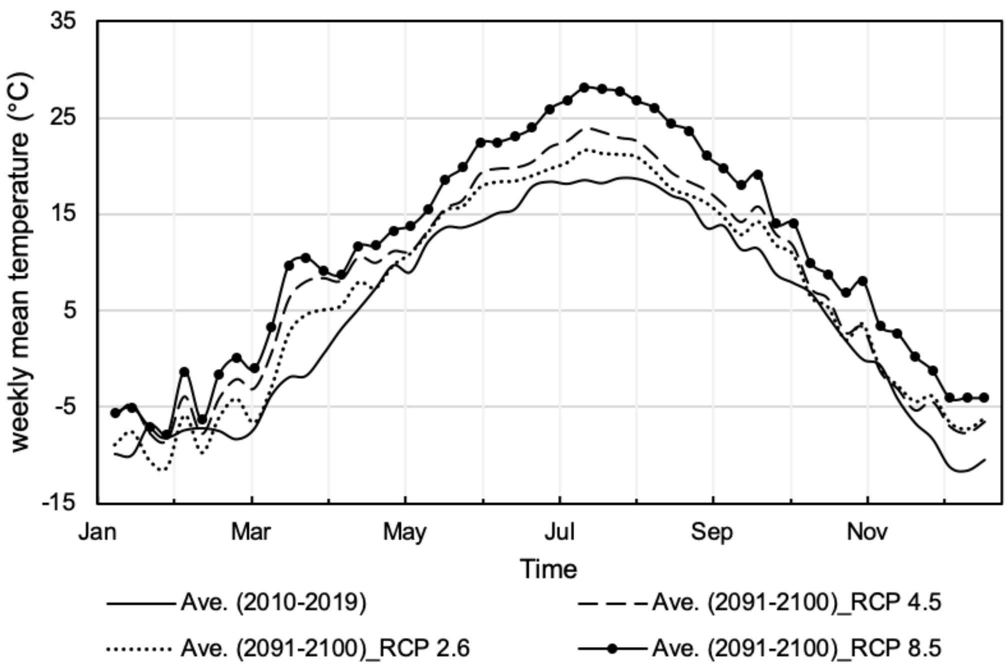


Fig. 5-6 Maximum temperatures for 2010-2019 vs. projections for 2091-2100 under three RCP scenarios

In terms of population, the total population of the Edmonton municipal region is calculated from the urban value and its share of the municipal total, which has stood at approximately 70% of the total regional population from 1981 onwards. Urban population data are from the City of Edmonton (2018). Further, the EMRB (2017) forecasts an urban population share of 70% under a low population growth scenario and a share of 66% in a high growth scenario by 2044, while the City of Edmonton (2018) projects an urban population share of 70% through 2066 in the high growth scenario. The growth rate ranges from 1.88% in the recent future to 1.3% at the end of the 21st century under the low growth rate scenario while for high growth scenarios, the growth rate varies from 2.37% to 1.5%. This study applies a 70% urban population share for both population scenarios throughout the projection period. Under these assumptions, the projected total population increases from 1.3 million in 2019 to 4 million in 2100 (or 208% growth) under a low population scenario and from 1.3 million in 2019 to 4.9 million in 2100 (or 277% growth) under a high population scenario (Fig. 5-7).

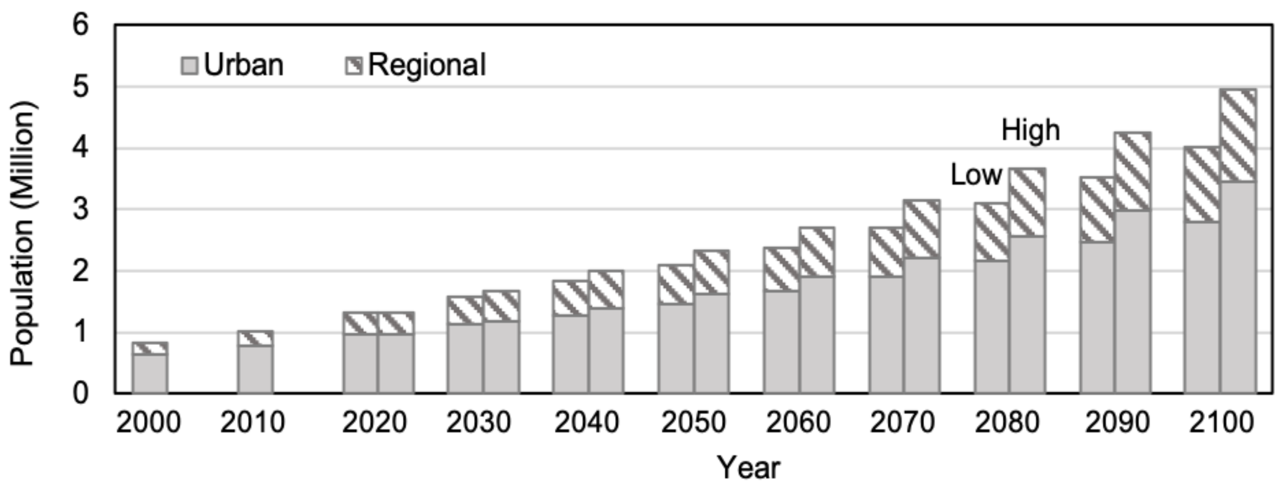


Fig. 5-7 Population of urban and regional area

The water conservation drivers focus on a few specific water conservation technologies. Water-saving appliances and plumbing fixtures as well as rain barrels have been installed in Edmonton and throughout North America over the last several decades (DeOreo, 2016); such installations are common across all scenarios and are assumed to continue to occur over the coming decades. Therefore, the conservation policies in the scenarios focus specifically on the effects of xeriscaping, greywater reuse and BAT, which are currently either uncommon (xeriscaping) or unimplemented (greywater reuse and the BAT) in Edmonton. Under the water conservation condition, with “additional” policy implementation, 80% of households are assumed to install the best available technology and greywater infrastructure, as well as xeriscaping, which together reduces per capita total water demands by 24% from 2019 to 2100. Under the no new policy condition, none of the above three policies is assumed to be adopted. However, per capita water demands will not remain constant with the present value. Instead, the existing policies are assumed to be gradually saturated so that reduction in water demand still occurs under the effect of existing policies. Note that the ICI sectors are excluded from the effect of the above new policies.

Based on the scenario settings described above, two sets of experiments were developed to 1) assess relative individual sensitivities of future water demands to the three key drivers, climate, population, and technology and policy, and 2) identify the plausible range of water demands to 2100 for the reference case, as well as for best and worst case scenarios. As described above, the three groups of sensitivity scenarios contain a pair of low and high scenarios in one dimension and hold the other two dimensions constant at their reference settings (see Table 5-1). The reference scenario represents a medium level of climate change (RCP 4.5), low population growth (1.3%-1.8% per year), and no additional water conservation policies. Further, the plausible range of demands to 2100 is investigated as a set of two bounding scenarios – best and worst cases (see Table 5-1) – and a reference case to demonstrate the combined effects of the three demand drivers.

Table 5-1 Scenario definitions

	Scenario Name	Definition			
		Climate Change	Population Growth	Technology	Notes
1	LC_LP_AP	RCP 2.6	Low population growth	Additional policies	Best case scenario
2	LC_LP_NP			No additional policies	Climate sensitivity group (low)
3	MC_LP_AP	RCP 4.5		Additional policies	Policy sensitivity group (additional)
4	MC_LP_NP			No additional policies	Reference case scenario; Population sensitivity group (low); Policy sensitivity group (no)
5	MC_HP_NP		High population growth		Population sensitivity group (high)
6	HC_LP_NP	RCP 8.5	Low population growth		Climate sensitivity group (high)
7	HC_HP_NP		High population growth		Worst case scenario

[a] Scenario name abbreviation: LC = low climate change, LP = low population growth, AP = additional water conservation policy, NP = no new policy, MC = medium climate change, HP = High population growth, HC = High climate change
[b] Climate abbreviation: RCP 2.6 = Low greenhouse gas emission level, RCP 4.5 = Medium greenhouse gas emission level, RCP 8.5 = High greenhouse gas emission level
[c] Additional policies = 80% Xeriscaping, 80% greywater reuse, new water saving technologies

Chapter 6 Results and Discussions

This chapter first introduces validation results for the models, and then investigates water demand predictors, and finally explores projections of long-term demands. Section 6.1.1 shows the performance of ANNs for short-term water demand forecasting, while section 6.1.2 displays the simulation accuracy of the hybrid model for long-term water demand forecasting. Further, based on the validated models, the effect of water demand predictors is investigated in section 6.2, including the relative importance of water demand drivers over the short term (section 6.2.1) and long term (section 6.2.2). Finally, section 6.2.3 focuses on combined effect of multiple drivers through developing bounding scenarios for the Edmonton region's water demand.

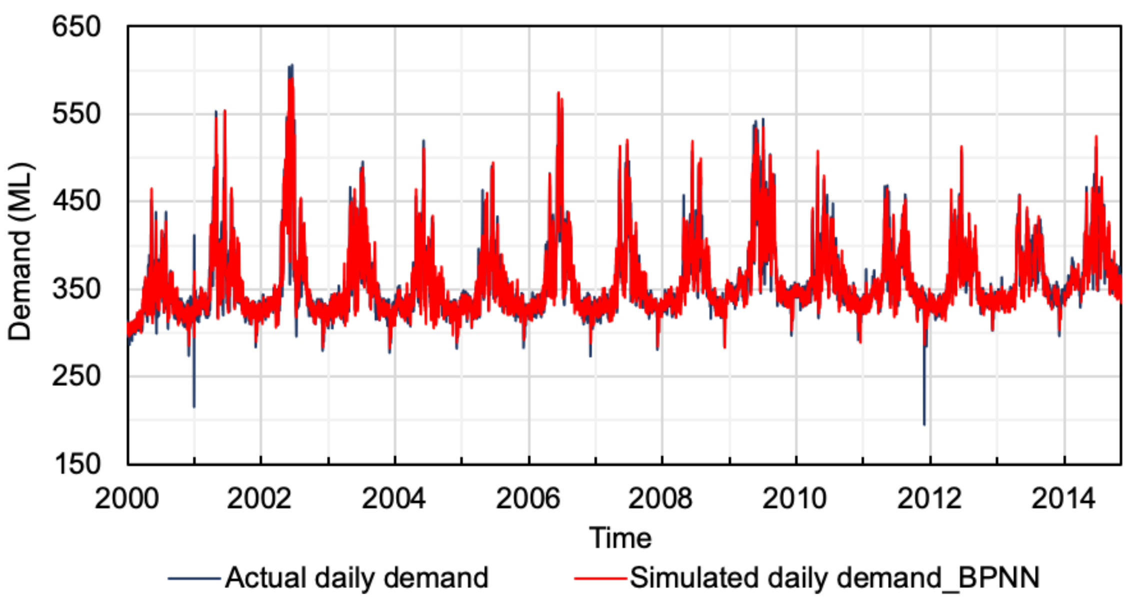
6.1 Validation Results

6.1.1 ANN Validation Results

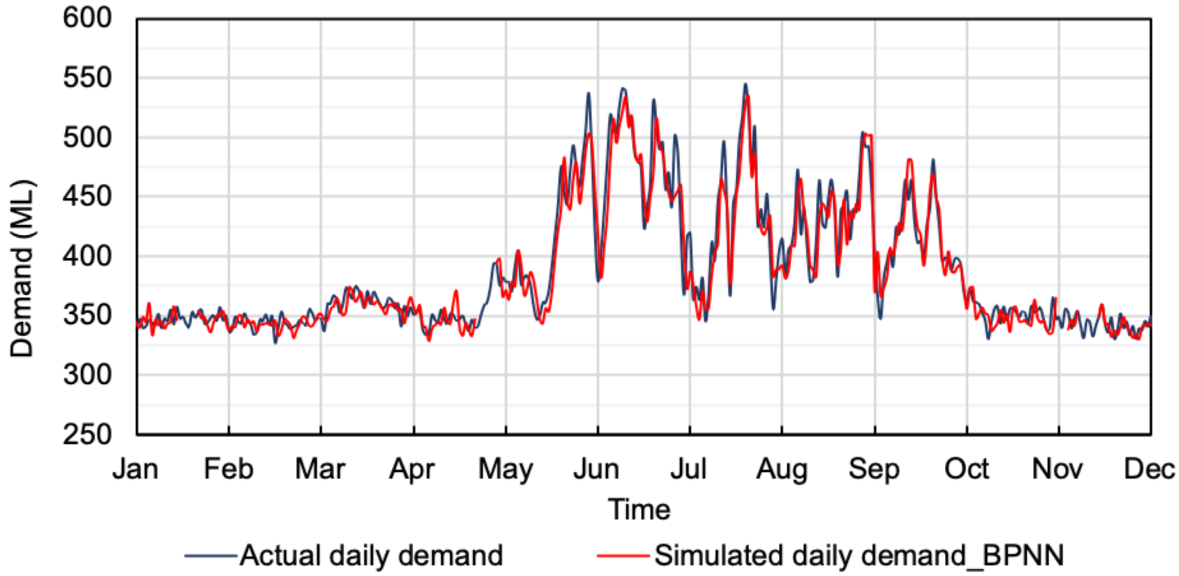
(1) Simulation Performance of the Optimum ANNs in Daily and Weekly Simulation

The optimum ANN for daily water demand forecasting found through the trial-and-error method was the BPNN model with 22 hidden neurons and following inputs: $D(d\text{-}1)$, $D(d\text{-}2)$, $T_{max}(d)$, $T_{max}(d\text{-}1)$, $T_{mean}(d)$, $T_{mean}(d\text{-}2)$, $P(d)$, *"day-in-week"* index and *"day-in-month"* index. Recall that D is the water demand, T_{max} is the maximum temperature, T_{mean} is the mean temperature, P is amount of precipitation, d is the day to be predicted, $d\text{-}1$ is one day before the day to be predicted, $d\text{-}2$ is two days before the day to be predicted, *"day in week"* is the index describing the number of the days in a week (i.e., 1 means Monday,…, 7 means Sunday) and *"day-in-month"* is the index describing the number of the days in a month (i.e., 1 means 1^{st},…, 31 means 31^{st}). The model performed well with MAE = 9.36 ML, RMSE = 12.79 ML, NRMSE = 3.66%, and R^2 = 0.92, while the historical average daily water demand was approximately 350 ML. Fig. 6-1(a) compares simulated values from the BPNN models with the actual observations from 2000 to 2014 at a daily scale, while Fig. 6-1(b) shows results for 2009 in greater detail.

For weekly water demand forecasting, the BPNN model with 62 hidden neurons and inputs of *D(w-1)*, *Tmean(w)*, *Tmean(w-1)*, *P(w)* and *P(w-1)* produced the best performance. Recall that *w* is the week to be predicted and *w-1* is one week before the week to be predicted. The statistical performance of the preferred BPNN included MAE = 63.73 ML, RMSE = 91.19 ML, NRMSE = 3.74%, and $R^2 = 0.89$, for an average historical weekly water demand of 2470 ML. The comparison between actual and simulated demand from 2000 to 2014 and the individual year 2009 is shown in Fig. 6-2 (a) and (b), respectively.



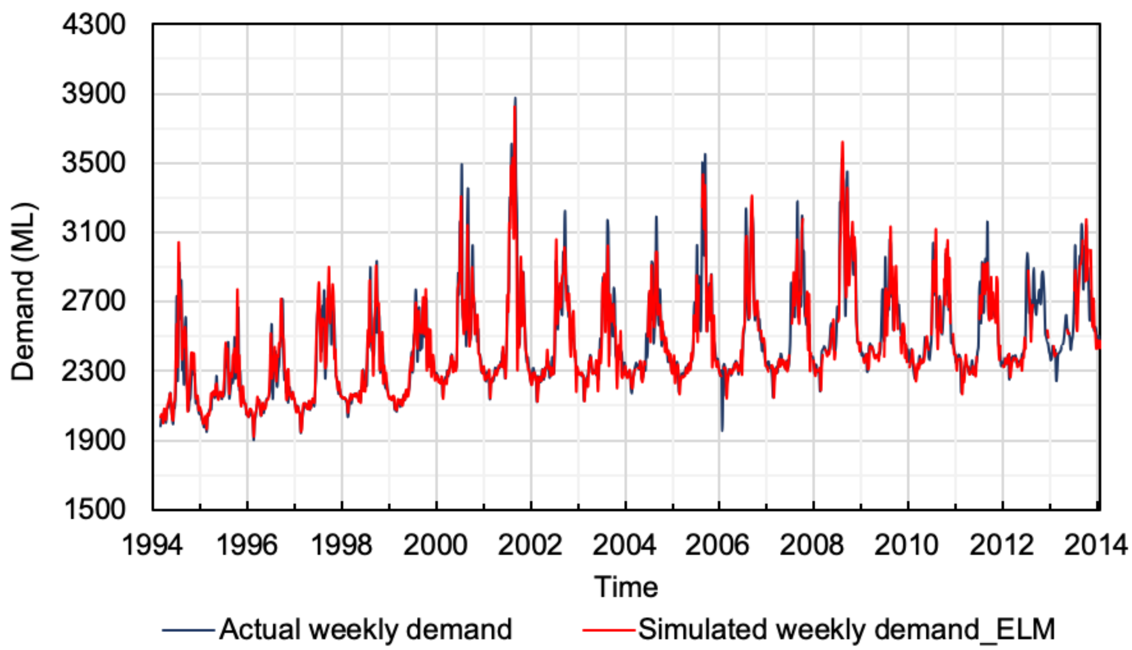
(a)



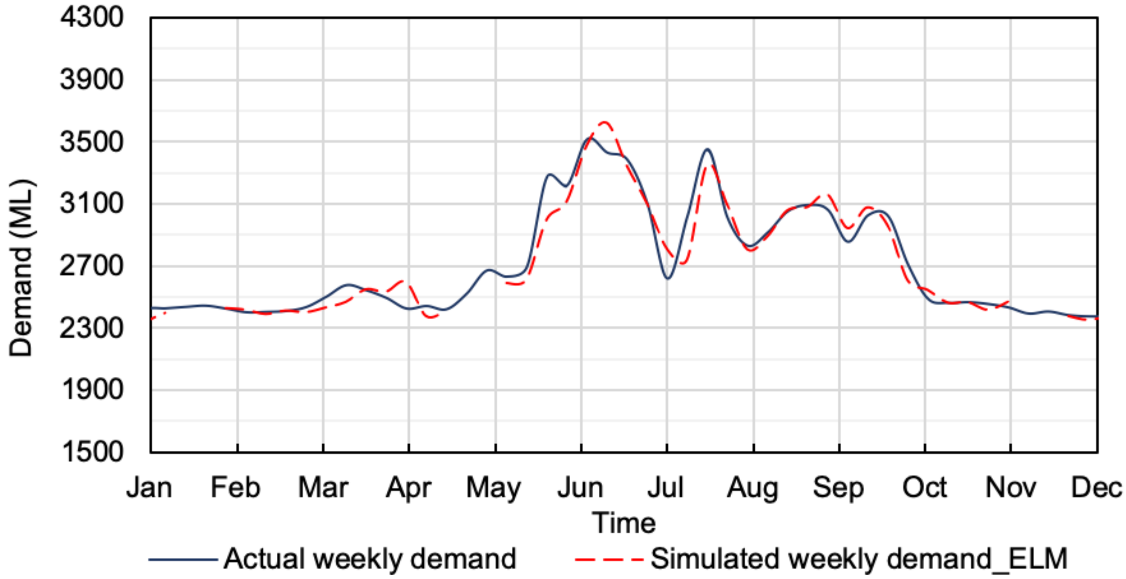
(b)

Fig. 6-1 Daily simulated results of the preferred BPNN

(a) from 2000 to 2014 (b) 2009



(a)



(b)

Fig. 6-2 Weekly simualted results of the preferred BPNN
(a) from 2000 to 2014 (b) 2009

(2) Comparison of the Results of MLR, BPNN and ELM

Through the selection process for the optimum models, the simulation performance of MLR, BPNN and ELM was compared. Table 6-1 provides some comparative results in daily water demand simulation. Clearly, the BPNNs and ELMs with optimal numbers of hidden neurons statistically outperformed the MLR models with all different input combinations. Fig. 6-3 compares the predictions produced by three models with the observations for 2007. The peaks were less accurately captured by MLR than the other two models. Among the ELM and BPNN models, the BPNN models produced slightly better results. For example, the BPNN model with *D(d-1, d-2)*, *Tmax(d, d-1)*, *Tmean(d, d-2)* ,*P(d,d-1)* and *OP(d-2)* produced a MAE of 9.55 ML, which was 0.34 ML lower than the value from the ELM. Similarly, the R^2 produced by the BPNN was slightly higher than the ELM value, which indicates a better ability to replicate historical observations. Note that similar conclusions were drawn in weekly simulation.

Importantly, although the performance of the ELM and BPNN differed only slightly, the optimum number of hidden neurons for BPNNs was significantly smaller than for the ELM. BPNN with fewer hidden neurons would require less work for adaptation to a different modeling framework, which made it more appropriate for integration with the SD model for long-term forecasting. In contrast, the training speed of the BPNN exceeded the time for the ELM by thousands of times, making it difficult to compare the two models. In this study, the aim was development of a simple but accurate ANN as a new component for the long-term hybrid forecasting model; therefore, the BPNN with a relatively smaller structure was preferred. However, for water utilities intending to develop new ANNs for regular operation, ELMs could be a good choice because of their faster learning speed.

Table 6-1 Comparison of BPNN, ELM and MLR in daily forecasting

Model	Hidden Neurons	MAE (ML)	RMSE (ML)	NRMSE (%)	R^2
BPNN	19	9.55	13.12	3.76	0.91
ELM	69	9.89	13.77	3.95	0.90
MLR	--	11.29	15.76	4.52	0.87

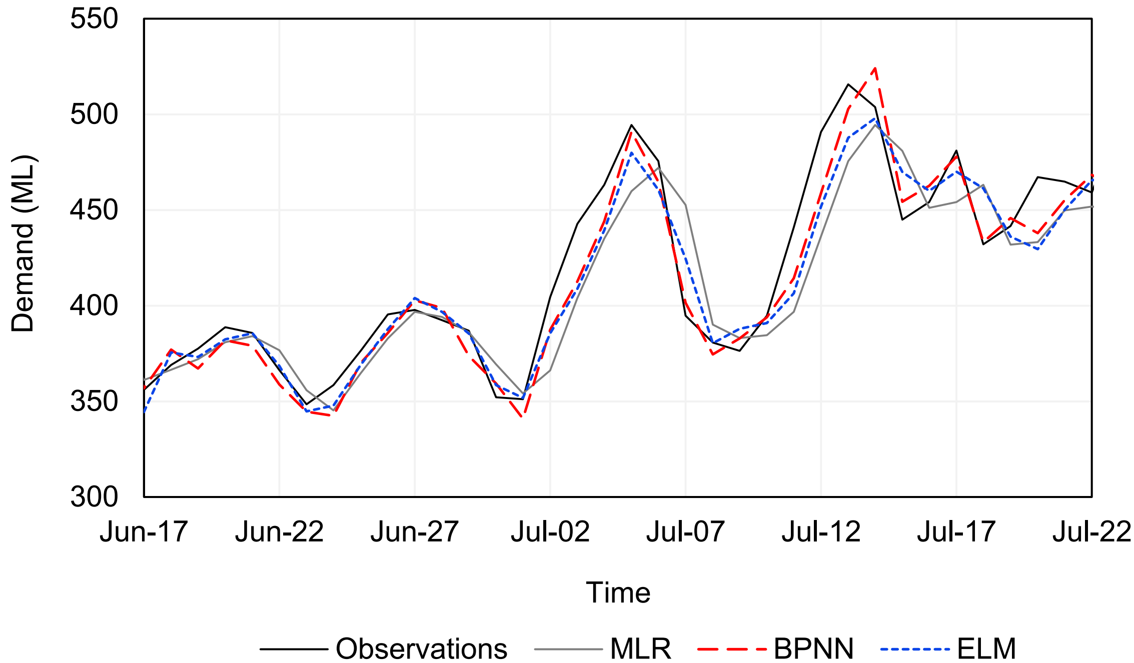


Fig. 6-3 Performance of daily MLR, BPNN and ELM in 2007

(3) Prediction Performance of the ELM and BPNN Models in Daily and Weekly Forecasting

EWSI examined the prediction ability of the selected daily time-step models from April to December 2019. Water professionals used the online user interface to obtain daily demand forecasts from the optimum BPNNs and ELMs and then checked the actual water use on the following day. Table 6-2 provides the 2-month evaluation of model performance for April and May 2019. On an average basis, both the BPNN and ELM functioned well, within -0.62% and -0.54% of the observed demand. The daily prediction error (PE) of predictions was observed to vary between -8.49 to 9.79% for the BPNN, and -7.27 to 11.13% for the ELM. The standard deviations of PE were low, with values of 3.2% and 3.6% for the BPNN and the ELM, respectively, which indicates a promising predictive capability of both models. Compared to the ELM, the

BPNN had a relatively larger mean error in daily prediction but the range between the lowest and highest errors was narrower. In contrast, the weekly forecast models generally presented a greater mean PE value than the daily models while their variability was reduced to between -5.09% to 0.26%. The weekly BPNN forecasting model outperformed the ELM in terms of the average error and the range of maximum and minimum errors. Standard deviations of errors for weekly prediction were not provided as they are less meaningful based on only 8 weeks of data. Overall, all four models presented strong predictive capabilities for practical use, and the BPNN models were slightly more reliable as the main forecasting tool because of their lower range of prediction errors.

Table 6-2 Prediction performance in April and May 2019

Error	Daily		Weekly	
	BPNN	ELM	BPNN	ELM
Mean PE	-0.62%	-0.54%	-1.97%	-2.33%
Maximum PE	9.79%	11.13%	0.26%	0.22%
Minimum PE	-8.49%	-7.27%	-3.91%	-5.09%
Standard deviation of PE	3.20%	3.60%	--	--

6.1.2 Hybrid Model Validation Results

(1) Simulation Performance of EWDS

The simulated results from EWDS for 2005-2015 matched historical observations with $R^2 = 0.81$, NRMSE = 4.82%, and MAE = 87 ML as compared with average observed weekly demands of 2471 ML. Fig. 6-4 compares the observed values with modeled water demands for Edmonton from

2005 to 2015. Overall, model estimates aligned well with the statistics, but a mismatch occurred in the winter season, because 1) no outdoor water is assumed to be used by residents during the winter and 2) the ANN model for outdoor demand is used only in the summer season; for these two reasons, the EWDS simulated constant water demand – with no fluctuations – in the winter. Note that the starting and ending points of winter seasons in EWDS differed every year based on the occurrence of freezing temperatures, as described in section 5.3.1 above.

The annual water demand of the four most important sectors is presented in Fig. 6-5. With the addition of regression models for ICI and multi-residential use, the simulated annual water demand matched well with the historical observed values, with R^2 = 0.84 and R^2 = 0.78 for the ICI and multi-residential sectors, respectively. The results for the regional sector had a lower R^2 = 0.66, because of data limitations (no disaggregation of data by water end use) for the customers around Edmonton. The simulated residential demand had a slightly lower R^2 than the other three sectors, because the unavailability of detailed data for individual end-use components specific to Edmonton (i.e. toilet, laundry, kitchen, shower, leaks and others) increased the difficulty of calibration.

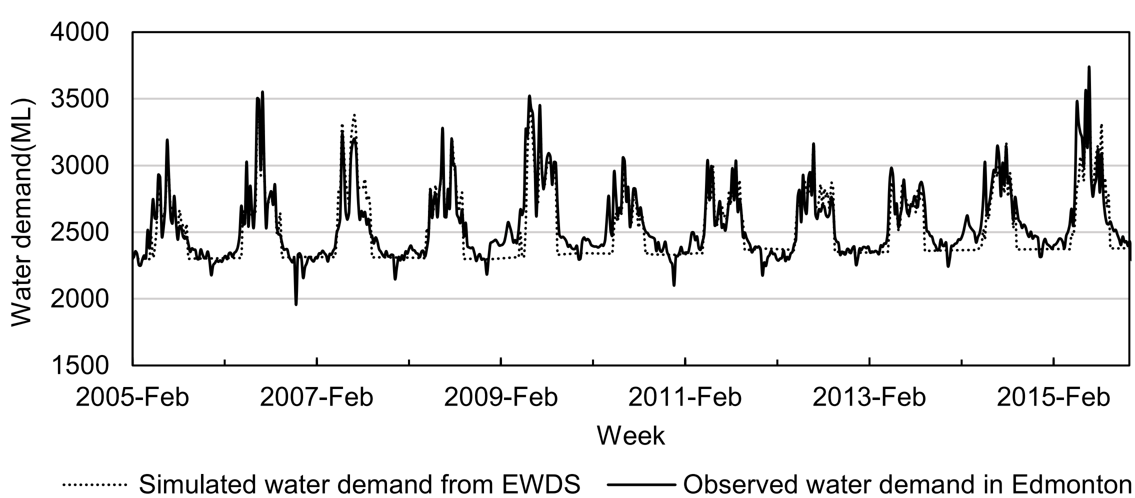
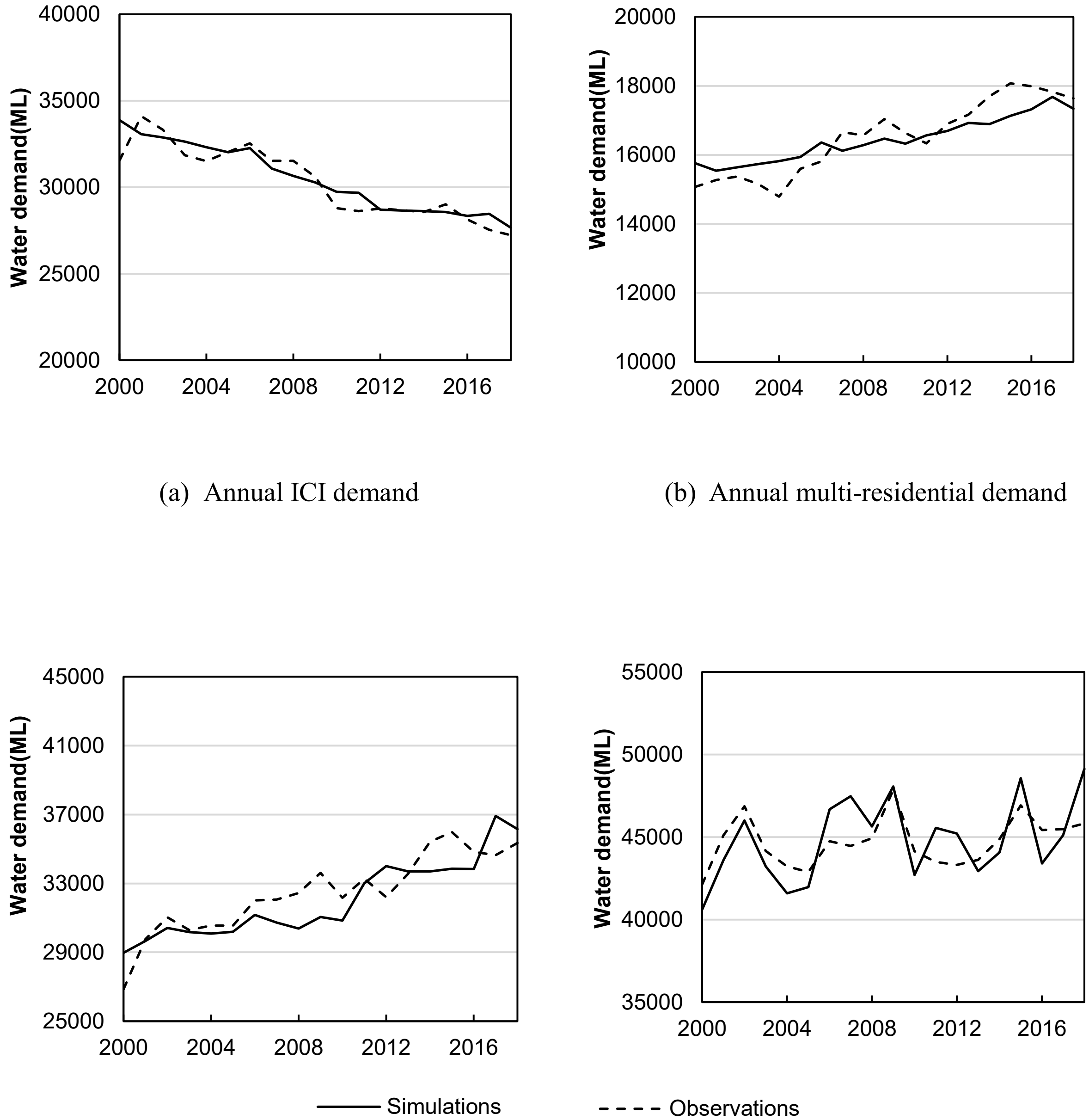


Fig. 6-4 Performance of EWDS



(a) Annual ICI demand

(b) Annual multi-residential demand

(c) Annual regional demand

(d) Annual residential demand

Fig. 6-5 Validated results of annual end-use demand

(2) Comparison of CWMM and EWDS

Although the CWMM and the EWDS simulated the water demands of two different cities, Calgary and Edmonton, the types and characteristics of data used in the two models are the same, which makes it useful to compare their results. Table 6-3 compares the original model (CWMM) with the improved hybrid model (EWDS) for 2005 to 2015. The average R^2 improved slightly from 0.79 to 0.83 while the R^2 for years such as 2006 and 2007 exceeded 0.9 in the EWDS. In addition, the NRMSE of EWDS significantly outperformed the CWMM over the whole simulated period and was reduced significantly from around 7.9% to 4.7%. In most years, the NRMSE values in EWDS were lower than 5% indicating low residual variance. EWDS therefore presented a more accurate simulation ability than the CWMM. Overall, the table clearly indicates that EWDS outperformed CWMM in replicating historical trends through the integration of the ANN and regression models.

Table 6-3 Comparison of CWMM and EWMM

Criteria	Model	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	**Ave.**
R^2	CWMM	0.62	0.83	0.87	0.84	0.81	0.75	0.80	0.87	0.78	0.87	0.70	**0.79**
	EWDS	0.77	0.91	0.92	0.9	0.86	0.74	0.82	0.88	0.81	0.77	0.80	**0.83**
NRMSE (%)	CWMM	11	8.3	7.2	7.6	7.9	7.1	6.5	6.2	8.1	4.46	6.75	**7.37**
	EWDS	4.2	4.1	4.6	3.4	7.1	5.3	3.7	3.4	3.8	5.75	6.13	**4.68**

6.2 Effect of Predictors and Drivers

6.2.1 The Relative Importance of Short-term Water Demand Predictors

To determine the most effective variables for daily and weekly forecasting and to find the optimum models, 102 and 44 different input combinations were examined for daily and weekly forecasting, respectively, using BPNN and ELM in this study. Note that the models in this section differ from the optimum models described in section 6.1.1, because they are designed to investigate the sensitivity of explanatory variables, rather than produce the best demand projections. This section shows sample results only from BPNN since the two models produced essentially the same conclusions in terms of the best predictor variables. The analysis of effective predictors in water demand forecasting was conducted in terms of temperature, precipitation and time indices.

(1) Temperature predictors

The water demand predictors were tested first. The model with water demand in previous day as the only input variable, or *D(d-1)*, produced good results with $R^2 = 0.8$; similarly, the R^2 produced by the model with only *D(d-2)* was 0.70, which indicates that *D(d)* and *D(d-1)* are important input variables for a daily forecasting ANN. Next, the effectiveness of 9 temperature predictors was tested through their sequential input with the demand predictors to the model. Table 6-4 compares the performance from multiple input combinations that contain only temperature predictors in daily forecasting models. The BPNN models used for testing the temperature predictors were named BP_T, for BPNN model with temperature predictors. BP_T_1 depended on maximum, minimum and average temperatures in addition to historical water consumption, and had the greatest R^2, a result that showed the importance of these predictor parameters. The MAE of BP_T_2, BP_T_3, BP_T_4 were 10.93, 10.07 and 9.82, respectively, which showed that among the three temperature predictors used, the maximum temperature was the most correlated variable with water demand while the minimum temperature was least correlated. Further, it was also observed that the MAE produced by BP_T_5 was as good as for BP_T_1 and that the RMSE was slightly lower. This result indicated that the minimum temperature as well as the maximum temperature in the previous two days and the mean temperature in the previous day were redundant inputs. The worse performance of BP_T_6 to BP_T_11, which contained those redundant inputs, also proved this point. Overall, comparison of multiple temperature input combinations revealed that the maximum and average temperatures produced more accurate results than the minimum temperature, most likely because outdoor watering in the summer is related more strongly to daytime average and high temperatures than to daytime low temperatures – as would be expected.

Table 6-4 Results of the comparative analysis on temperature predictors (Daily)

Inputs		Model	HN	MAE (ML)	RMSE (ML)	NRMSE (ML)	R^2
1	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1, d\text{-}2), T_{min}(d, d\text{-}1, d\text{-}2), T_{mean}(d, d\text{-}1, d\text{-}2)$	BP_T_1	34	9.69	13.66	3.92	0.90
2	$D(d\text{-}1, d\text{-}2), T_{min}(d, d\text{-}1, d\text{-}2)$	BP_T_2	34	10.93	15.75	4.51	0.87
3	$D(d\text{-}1, d\text{-}2), T_{mean}(d, d\text{-}1, d\text{-}2)$	BP_T_3	44	10.07	14.43	4.14	0.89
4	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1, d\text{-}2)$	BP_T_4	34	9.82	13.87	3.98	0.90
5	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2)$	BP_T_5	49	9.69	13.63	3.90	0.91
6	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}1)$	BP_T_6	49	9.75	13.71	3.93	0.90
7	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}2), T_{mean}(d, d\text{-}1)$	BP_T_7	49	9.75	13.69	3.92	0.90
8	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{min}(d, d\text{-}1)$	BP_T_8	37	10.83	15.62	4.48	0.87
9	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{min}(d, d\text{-}2)$	BP_T_9	49	9.73	13.62	3.90	0.91
10	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}2), T_{min}(d, d\text{-}1)$	BP_T_10	40	9.71	13.61	3.90	0.91
11	$D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}2), T_{min}(d, d\text{-}2)$	BP_T_11	40	9.78	13.67	3.92	0.91

Note: HN = Hidden Neurons

For weekly models, the results were quite different. The mean temperature was found to be more effective than the minimum and maximum temperature in weekly water demand forecasting, as shown through a comparison of the performances of BP_T_12, BP_T_13 and BP_T_14 (see Table 6-5), with MAE values of 68.45, 76.34 and 81.59, respectively. BP_T_15 produced a greater MAE than BP_T_12, which indicated that combining the three temperature predictors as inputs did not produce better results than use of the mean temperature only. The MAE values of BP_T_16 and BP_T_17 were quite close, which demonstrated that the minimum temperature and the maximum temperature were redundant for weekly water demand forecasting. It was not surprising that the weekly municipal water demand depended significantly on the mean weekly temperature, since a high average temperature indicates more hot days and will then lead to more water demand for outdoor watering.

Table 6-5 Results of the comparative analysis on temperature predictors (Weekly)

Inputs	Model	HN	MAE (ML)	RMSE (ML)	NRMSE (ML)	R^2
1 $D(w\text{-}1), T_{mean}(w, w\text{-}1)$	BP_T_12	49	68.45	101.64	4.16	0.87
2 $D(w\text{-}1), T_{max}(w, w\text{-}1)$	BP_T_13	74	76.34	113.86	4.66	0.84
3 $D(w\text{-}1), T_{min}(w, w\text{-}1)$	BP_T_14	96	81.59	124.88	5.11	0.81
4 $D(w\text{-}1), T_{max}(w, w\text{-}1), T_{min}(w, w\text{-}1), T_{mean}(w, w\text{-}1)$	BP_T_15	72	69.49	99.64	4.10	0.87
5 $D(w\text{-}1), T_{max}(w, w\text{-}1), T_{min}(w, w\text{-}1), T_{mean}(w, w\text{-}1), P(w, w\text{-}1)$	BP_T_16	9	64.45	91.77	3.77	0.90
6 $D(w\text{-}1), T_{mean}(w, w\text{-}1), P(w, w\text{-}1)$	BP_T_17	62	63.73	91.19	3.74	0.89

Note: HN = Hidden Neurons

Precipitation predictors

The importance of precipitation as a water demand predictor was tested, with results shown in Table 6-6. Note that the BPNN models used for testing the precipitation predictors were given names beginning with BP_P, for BPNN model with precipitation predictors. A comparison of BP_P_2 and BP_P_3 with BP_P_1 reveals that both the amount of precipitation and the occurrence of precipitation increased prediction accuracy, with the MAE reduced from 9.69 ML to 9.46ML and 9.56 ML, respectively. The amount of precipitation was more effective than the occurrence of precipitation. However, two precipitation predictors were included in BP_P_4 and the result was poorer than BP_P_2, which only contained the amount of precipitation. Therefore, a single precipitation predictor was found to be sufficient for water demand forecasting.

Further, the use of only precipitation predictors presented a much worse result than for temperature predictors, as shown by BP_P_5 – a result that indicated that precipitation occurrence and amount were weak predictors for daily water demand if used without temperature variables. Further, BP_P_6 to BP_P_10 investigated the forecasting value of including a longer period of five days for precipitation occurrence. The result was that only the precipitation occurrence on the current date improved predictions and decreased errors, while the inclusion of previous days did not improve results, but rather led to a decrease in R^2 from 0.91 to 0.90. Overall, among the precipitation predictors, the occurrence of precipitation and the amount of precipitation were most effective when they were used with temperature predictors.

Similarly, sample results for weekly forecasting models are shown in Table 6-7, and were similar to those from the daily analysis. However, the precipitation amount, and not the precipitation occurrence, improved simulation performance, as shown by a comparison of BP_P_12 and BP_P_13 with BP_P_11. Further, the model that included only the precipitation amount produced the best results among all models in the table. This finding that precipitation amount was better correlated with water demand than precipitation occurrence matches that of Bougadis et al. (2005), but is the opposite result to Adamowski & Karapataki (2010) and Jain et al. (2001). The reason may be related to climate conditions of the study areas – Ottawa, Canada in Bougadis et al. (2005), Nicosia, Cyprus in Adamowski & Karapataki (2010) and Kanpur, India in Jain et al. (2001). The climates of Edmonton and Ottawa are similar, with average monthly temperature ranging from -10°C to 20°C and average monthly precipitation in summer varying slightly in each month over a general range of 40mm to 80mm (Climate Data, 2012). In contrast, the temperatures in Kanpur and Nicosia are between 10°C and 30°C year-round, while Nicosia experiences little precipitation (0-20mm) and Kanpur has extremely variable precipitation (5-280mm) (Climate Data, 2012). Therefore, the amount of precipitation either plays a minor role in water demand forecasting or incorporates too much variation. Regardless, precipitation volume was a better predictor in study areas with similar climate conditions to Edmonton.

Table 6-6 Results of the comparative analysis on precipitation predictors (Daily)

Inputs	Model	HN	MAE (ML)	RMSE (ML)	NRMSE (%)	R^2
1 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2)$	BP_P_1	49	9.69	13.63	3.90	0.91
2 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), P(d)$	BP_P_2	47	9.46	13.03	3.73	0.91
3 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d)$	BP_P_3	18	9.56	13.25	3.80	0.91
4 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), P(d), OP(d)$	BP_P_4	44	9.47	13.16	3.77	0.91
5 $D(d\text{-}1, d\text{-}2), P(d), OP(d)$	BP_P_5	8	11.36	15.95	4.57	0.87
6 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d\text{-}1)$	BP_P_6	41	9.81	13.81	3.96	0.90
7 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d\text{-}2)$	BP_P_7	36	9.76	13.80	3.96	0.90
8 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d\text{-}3)$	BP_P_8	41	9.78	13.72	3.93	0.90
9 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d\text{-}4)$	BP_P_9	29	9.78	13.82	3.96	0.90
10 $D(d\text{-}1, d\text{-}2), T_{max}(d, d\text{-}1), T_{mean}(d, d\text{-}2), OP(d\text{-}5)$	BP_P_10	41	9.81	13.71	3.93	0.90

Note: HN = Hidden Neurons

Table 6-7 Results of the comparative analysis on precipitation predictors (Weekly)

Inputs	Model	HN	MAE (ML)	RMSE (ML)	NRMSE (%)	R^2
1 $D(w\text{-}1), T_{mean}(w, w\text{-}1)$	BP_P_11	49	68.45	101.64	4.16	0.87
2 $D(w\text{-}1), T_{mean}(w, w\text{-}1), OP(w, w\text{-}1)$	BP_P_12	16	69.40	101.74	4.17	0.87
3 $D(w\text{-}1), T_{mean}(w, w\text{-}1), P(w, w\text{-}1)$	BP_P_13	62	63.73	91.19	3.74	0.89
4 $D(w\text{-}1), T_{mean}(w, w\text{-}1), P(w, w\text{-}1), OP(w, w\text{-}1)$	BP_P_14	48	64.64	91.97	3.77	0.90

Note: HN = Hidden Neurons

Time Indices

The periodicity of water demand was tested though addition of time indices to the model inputs, an approach that was rarely used in previous literature. As shown in Table 6-8, all three model types (BPNN, ELM, and MLR) that used indices (i.e. *"day-in-week"*, *"day-in-month"*) produced significantly better results than those without indices for daily water demand simulation. For the BPNN, MAE decreased from 10.48 to 9.58 and R^2 increased from 0.89 to 0.91, which demonstrates the periodicity of water demand over both the week and the month. These time indices could offer the ANNs new information to aid their learning of water demand patterns that change over the course of a week or month. Such indices are highly recommended for incorporation in future research. The time indices including *"week-in-month"* and *"week-in-year"* were also tested in weekly simulations, but did not produce better results, indicating that weekly demand does not show significant periodicity over the course of a month or year.

Table 6-8 Comparisons between Three Daily Models with Indices and without Indices

Inputs	Model	HN	MAE (ML)	RMSE (ML)	NRMSE (%)	R^2
D(d-1, d-2), T_{max}(d, d-1), T_{mean}(d, d-2), P(d,d-1), OP(d-5)	MLR	\	11.74	16.51	4.73	0.86
	BPNN	18	10.48	14.57	4.18	0.89
	ELM	41	10.83	15.20	4.36	0.88
D(d-1, d-2), T_{max}(d, d-1), T_{mean}(d, d-2), P(d,d-1), OP(d-5), "day-in-week", "day-in-month"	MLR	\	11.32	15.79	4.53	0.87
	BPNN	19	9.58	13.15	3.77	0.91
	ELM	69	10.01	13.96	4.00	0.90

6.2.2 The Relative Importance of Long-term Forecasting Demand Drivers

Three sensitivity scenario groups were developed to examine the relative importance of long-term forecasting demand drivers (i.e., population, climate change and policy implementation) using the validated hybrid model. The scenario settings were described in section 5.4. Fig. 6-6 presents annual municipal water demands under the sensitivity experiments, with high and low population growth, climate change, and water conservation policy scenarios. By 2100, the hybrid model simulated water demand ranges under high and low climate change, population, and water conservation policy scenarios from 3.3-3.7 × 10^5 ML (million liters), 3.4-4.1 × 10^5 ML, and 2.9-3.4 × 10^5 ML, respectively. These differences between low and high cases amounted to 12%, 20%, and 17%, respectively. Among the three factors, only conservation policy implementation reduced water demand while the climate and population growth drove increases. The strongest driver of water demand for the Edmonton region water service area was therefore population, while the least sensitive driver was climate change. This result for climate change was not surprising, since outdoor water use in the Edmonton region is currently responsible for only approximately 2% of the total annual demand. However, the conclusion may differ in cities with large proportions of outdoor water use such as Denver, Colorado, where the climate-driven outdoor water use occupies 62% of total water consumption (DeOreo, 2016).

The three drivers also affected demand differently. Specifically, population affected the total demand while climate change and policy drove changes in per capita demands. However, water resource management clearly does not control urban and regional population growth; population changes occur because of demographic and economic drivers, for example. The second driver – policy adoption – could be affected by personal behaviors or water utilities' decisions through "soft-path" water management (Gleick, 2003). Soft-path approaches focus on reducing demand through inducing institutional and behavioral changes (Larson et al., 2016), including the adoption of water-use practices and efficient technologies such as adoptions of “low-flow” fixtures and appliances, educational campaigns, water metering and consumption feedback, leak detection programs, economic incentives, xeriscaping, and water treatment and reuse (Billings & Jones, 2008; DeOreo et al., 2016; Sønderlund et al., 2016) while hard-path approaches in water management aim to manage water supply through embodying traditional technological and structural fixes such as dams and other infrastructure used for water treatment, storage, and flood control. Among the three water conservation options, xeriscaping was less effective because of the small percentage of outdoor use in Edmonton, and because the adoption of xeriscaping depends on personal preferences. Greywater reuse and the best available technology resulted in greater reductions in water demand, and such adoptions depend on large-scale infrastructure programs or development within the control and management of water utilities. Overall, water conservation efforts and technological progress can play a significant role in municipal water management to counteract the rapid rise of water demand with population growth and climate change. The cost of technology implementation is also an important consideration for decision makers in water management and the effect of implementation cost should be included in future study (Chohin-Kuper et al., 2002).

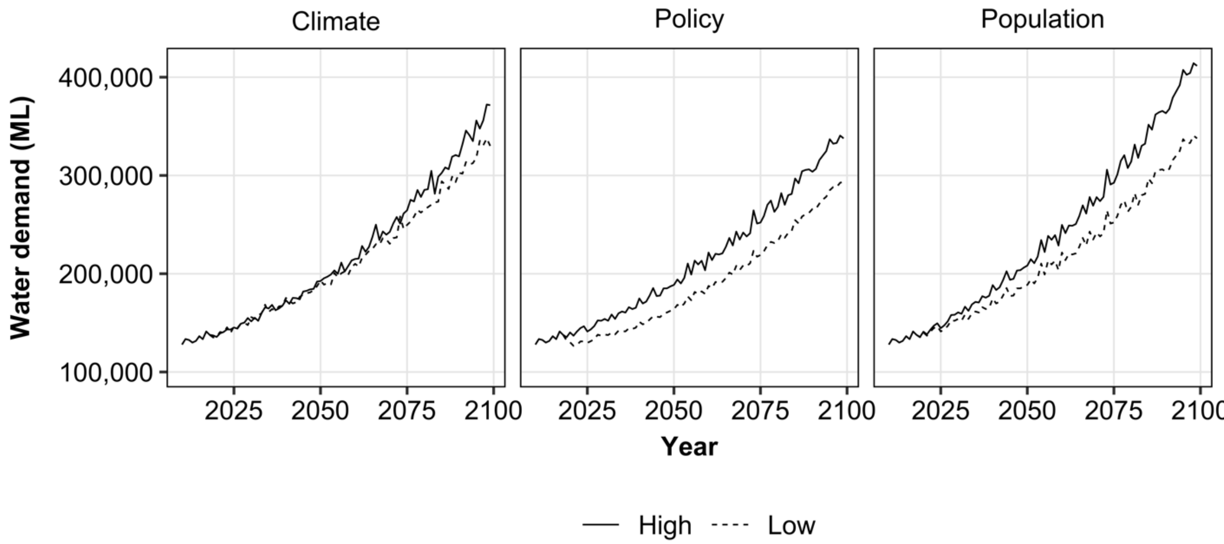


Fig. 6-6 Effect of three demand drivers on water demand

The climate change scenarios also revealed a significant difference in the length of the outdoor water use period. Fig. 6-7 (a) and (b) compare average total weekly water demands and per capita weekly water demands for 2010-2019 with the demands in 2091-2100 as driven by RCP 2.6, RCP 4.5, and RCP 8.5 climate conditions. Compared to RCP 2.6, the outdoor watering period under RCP 8.5 was about 5 weeks longer in 2019-2100 period. With temperature remaining above zero degrees for longer, the growing season shown in the model was reasonably longer. The peak of average weekly water demand for the 2010-2019 period was 3011 ML/week, while the value of the 2091-2100 period under RCP 2.6, RCP 4.5 and RCP 8.5 was 7966 ML/week, 8043 ML/week and 9392 ML/week, respectively. Interestingly, although the average total weekly water demand of the 2010-2019 period was lower than the demands of the 2091-2100 period under all three scenarios because of the larger future population, the average per capita weekly demand of the most recent 10 years was significantly higher than that of 2091-2100 under three scenarios, because the existing water conservation policies were gradually implemented and reduced the per capita water demand by the end of 21 century. Per capita weekly demand under RCP 8.5 was almost as high as the current values. Although severe climate change was expected to increase the summer per capita outdoor water demand significantly, the water demand reduction from the existing conservation policies greatly counteracted such increases.

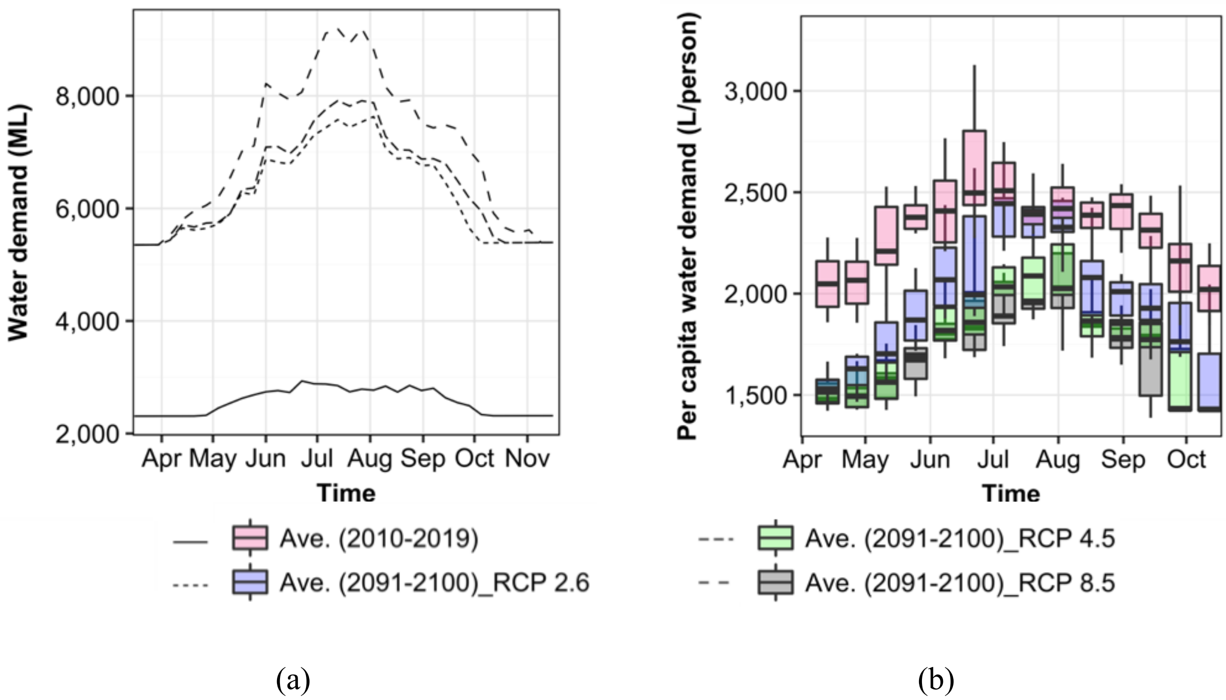


Fig. 6-7 Changes in (a) total weekly water demand and (b) per capita weekly water demand for 2010-2019 vs. the three RCP scenarios in 2091-2100

6.2.3 Bounding Water Demand Scenarios

Three bounding water demand scenarios were established to present the combined effects of multiple demand drivers. Under the worst-case scenario (HC_HP_NP) described in section 5.4, which has a high population growth rate, high degree of climate change, and no water conservation effort, the total annual municipal demand reached 4.5×10^5 ML in 2100 (see Fig. 6-8), which represents an increase of 246% from 2019 levels of 1.3×10^5 ML. Under the reference scenario (MC_LP_NP), the annual water demand reached approximately 3.4×10^5 ML, for an increase in water demand of 162% between 2019 and 2100. Finally, in the best-case scenario (LC_LP_AP), annual water demand increased to 2.9×10^5 ML in 2100 because of a relatively lower population, less climate change, and the adoption of additional water conservation policies; this demand represents a 123% increase from 2019. Meanwhile, the per capita water demand decreased by 13%, 23%, 43% from 2019 to 2100 under the worst-case, reference and best-case scenarios, respectively.

The results also permit a comparison of the effects of the three drivers. In the worst-case scenario, the water demand doubled over the 48 years from 2019-2066 (see the horizontal line in Fig. 6-8), while this doubling only occurred in the reference and best-case scenarios by 2079 and 2095, respectively. In other words, there was a 30-year difference in the doubling time of water demand between the best-case and worst-case scenarios.

This difference has significant implications for water infrastructure planning and depends both on factors outside the control of municipal decision makers (population growth and global climate change) and within their control, such as those technology adoptions and human behaviors they can influence through education and enforcement (rationing and water conservation behaviors), technological or policy change (adoption of new technologies with building codes, water pricing, and subsidization of appliances and fixtures), and infrastructural change (xeriscaping and greywater reuse) (Rasoulkhani et al., 2018; Renwick & Archibald, 1998; Wang & Davies, 2018; Wang et al., 2016). Additionally, the EWDS makes clear the effects of each of these changes, both in the near term at a weekly time step, and over the long term to 2100. When only climate was permitted to differ from the reference scenario, the doubling occurred by 2078 and 2085 under the HP_LP_NP and LP_LP_NP, or 1 year earlier and 6 years later than the reference doubling time, respectively. In terms of the effect of population change, a high population (MC_HP_NP) drove the water demand to double by 2072, which was 7 years earlier than in the reference scenario. Finally, from a policy perspective, the implementation of the three additional conservation policies, xeriscaping, greywater reuse and the best available technology (MC_LP_AT), delayed the doubling to 2093, which was a 13-year delay from the reference scenario.

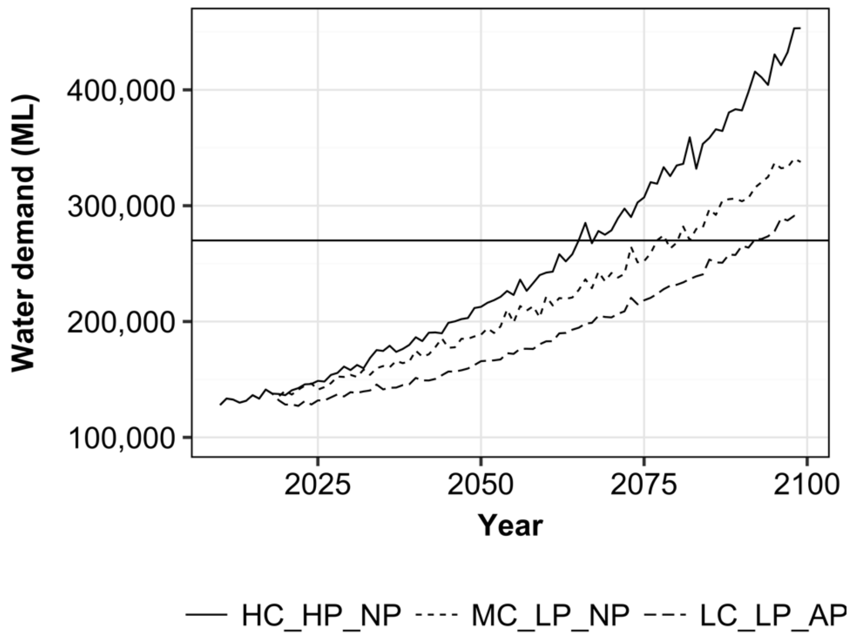


Fig. 6-8 comparison of three bounding scenarios

The distributions of end-use water demand in 2100 under three bounding scenarios as well as the current year (2019) are compared in Fig. 6-9. The size of the pie represents the total per capita demand. Compared to its simulated value of 283 L/person/day in 2019 the total per capita water demand decreased to 251 L/person/day, 231 L/person/day, and 198 L/person/day in 2100 under LC_LP_AP (best-case), MC_LP_NP (reference), and HC_HP_NP (worst-case) as a result of existing or plausible policies. This result is consistent with the fact that a decrease in per capita water demand has been observed over the past decades in Edmonton (EWSI, 2018). Finally, in terms of technological change, the portion of multi-residential and toilet demand under LC_LP_AP was 10% of the total demand and 6% of the residential demand, respectively, while the two no-policy scenarios simulated multi-residential demand as 11% and 13% of the total demand and the toilet demand as 18% of the residential total. These results suggest that greywater reuse and the BAT were effective in reducing indoor water demand.

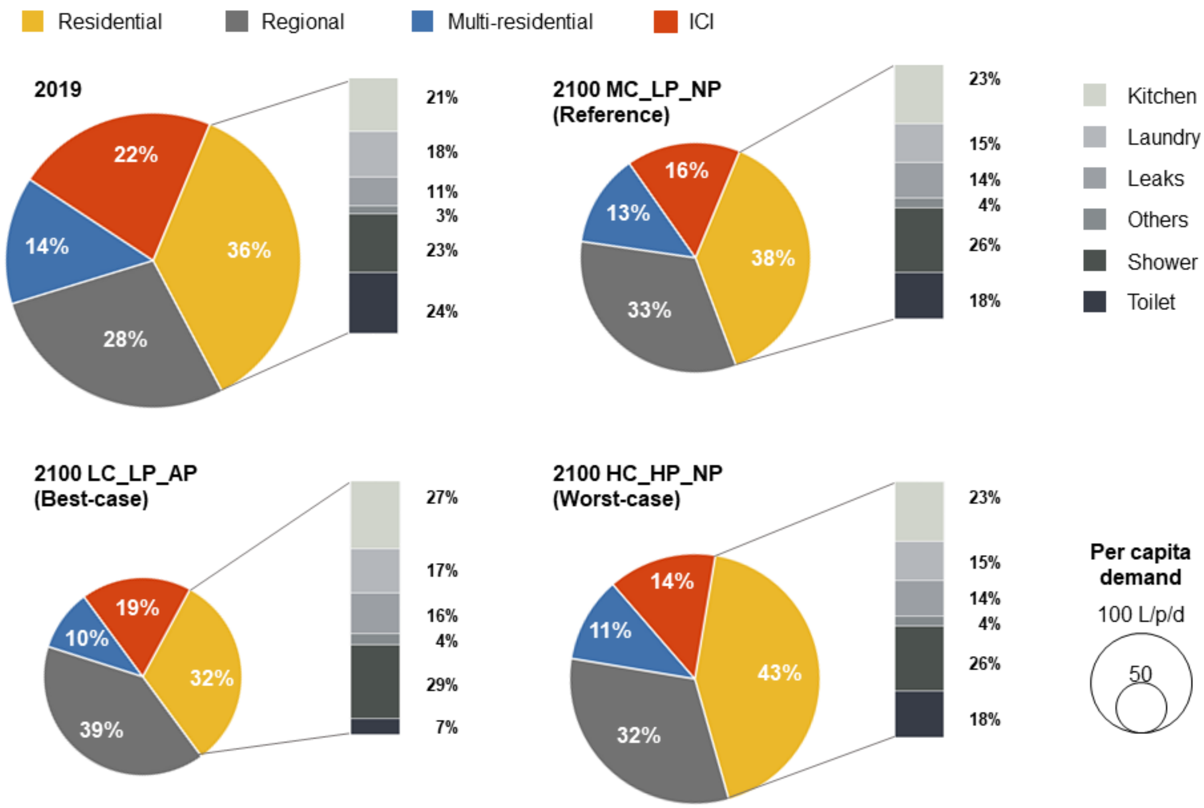


Fig. 6-9 Water demand distribution in 2019 vs 2100 under the three bounding scenarios (the size of the pie represents the total per capita demand)

Chapter 7 Conclusions and Future work

This thesis introduced two novel simulation approaches for water demand forecasting, as alternatives to conventional methods. The major products of this study included 1) accurate ANN models for daily water demand forecasting, and 2) a hybrid SD-ANN-regression forecasting model of the Edmonton region water service area's long-term water demand to 2100. The incorporation of data-driven models (i.e. artificial neural networks and regression models) with a structural system dynamics model for municipal demand projection is a novel contribution.

Firstly, artificial neural networks were proven to be a useful tool in short-term forecasting. Study outputs included a user-friendly application developed for EWSI based on the optimum daily and weekly artificial neural networks. ANNs presented excellent ability in predicting water demand, with an average of 3.66% and 3.74% error in daily and weekly simulation over the 2005-2015 period, and with an average of 0.62% and 1.97% error in daily and weekly prediction from April to May 2019. Two types of ANN developed in this study, BPNN and ELM, outperformed the conventional multiple linear regression model, producing around 2 ML lower error than the MLR. The optimum BPNN produced slightly more accurate predictions and had less hidden neurons than the ELM; it was therefore chosen for further integration into the long-term model.

The importance of water demand drivers for short-term forecasting was examined in this study. Previous water demands are the most effective predictors in short-term water demand forecasting. Water demands of one day and two days before the day to be predicted both produced a R^2 higher than 0.7 while they are used as the only predictor in the ANN. Among three possible temperature predictors, maximum temperature was the most correlated variable with daily water demand, while mean temperature was the second and the minimum temperature was the least correlated. The MAE from the daily forecasting models with maximum temperature, mean temperature and minimum temperature in addition to two water demand predictors were 10.93 ML, 10.07 ML, and 9.82 ML, respectively. For weekly forecasting, mean temperature was more effective in predicting water demand than the other two temperature predictors. Further, the use of Edmonton's precipitation amount as a predictor produced better results than the precipitation occurrence in daily forecasting model with MAE values of 9.46 ML and 9.56 ML, respectively. The academic literature provides conflicting results in terms of the relative importance of precipitation amount and occurrence; therefore, it is likely that the importance of the two predictors depends on climatic conditions in the study area. Finally, time indices related to the day of the week and the day of the month helped to better predict the water demand, and increased the R^2 values from 0.89 to 0.91. The improvement from time indices showed significant periodicity of water demand over the course of a day or a month. Such indices are highly recommended for incorporation in future research.

Secondly, the Edmonton Water Demand Simulator (EWDS) proved a powerful tool for long-term municipal water demand forecasting. The EWDS is an end-use based hybrid model with a weekly time step, and is composed of a system dynamics model, regression models and an artificial neural network model. Its end-use framework includes ten end uses for both urban and regional water demands: 6 residential indoor uses, outdoor residential use, non-revenue use, ICI use, and multi-residential use. The EWDS produced accurate simulations of municipal water demand over the validation period of 2005-2018, as demonstrated by model statistics including $R^2 = 0.81$ and MAE of 87 ML for an average weekly demand of 2471 ML.

Using the EWDS, this study investigated the effect of changing climatic conditions, increasing population, and policies adopted for water conservation in the Edmonton region water service area on the future water demand to 2100. The reduction in water demand was analyzed using water conservation policies. Conservation policies that were tested included implementing highly efficient appliances, xeriscaping, and greywater treatment and reuse. The water demands were compared under all the different policies, climate change, and population growth scenarios, in terms of their overall effects and their relative importance. Additionally, bounding scenarios were developed as best and worst cases.

Based on the findings of this research, the following conclusions can be drawn for the relative importance examination:

1) Population was the most effective driver of water demand over the long term. High and low population growth resulted in 20% difference of water demand in 2100. With a slow population growth rate, the water demand under current policy condition and medium climate change (RCP 4.5) increased by 162% by 2100 and doubled at 2079;
2) Water conservation measures, as evaluated, were second most effective in reducing the per capita water demand, which led to a 17% decrease in water demand through implementing three potential water-saving policies compared to "no additional policy" condition. Policy makers should consider a combined use of water saving technologies to increase potential savings in municipal water use; and,
3) More severe climate change conditions caused a longer watering season but slight difference (12%) of water demand resulted in high (RCP 8.5) and low (RCP 2.6) climate change. The minor impact of climate on water demand resulted in the limited outdoor water use (2% of municipal total). Conclusions may differ in other cities with a higher portion of outdoor water consumption.

Through a bounding scenario analysis, the combined effect of multiple water demand drivers identified the plausible range of water demands to 2100. Respectively, 246%, 162%, and 123%

increases in water demand were reached by 2100 under the worst-case, reference, and best-case scenarios. The water demand doubling times were used as indicators for evaluating water demands. This doubling occurred in the worst-case, reference, and best-case scenarios by 2066, 2079 and 2095, respectively. Thus, there was a 30-year difference in the doubling time of water demand between the best-case and worst-case scenarios. The implementation of the three additional conservation policies, xeriscaping, greywater reuse, and a best available technology, delayed the doubling time to 2093 compared to the reference scenario, which was a 13-year delay.

This hybrid model was developed as a part of a long-term effort to engage water managers and policy makers on the broad choices of policies that could be used to influence water use behaviors. This can be accomplished by implementing various policies that were evaluated in this study as well as a variety of other water reduction mechanisms including educating consumers, providing incentives for lower water use, reducing leakage, ICI reuse and rainwater harvesting. Although the study focused on the Edmonton region water service area, demand management policies used in the study can be considered for other regions to achieve the long-term sustainability of water resources.

Recommendations

Future research should address some limitations of this study. Firstly, the unavailability of data, such as adoption rates of low-flow appliances and xeriscaping, limits the study to applying values from large-scale studies that did not include Edmonton. Further, because details of regional water use are unavailable – EWSI sells water outside the city, and therefore does not track regional water end uses – the simulation of the regional water demand is approximate, so that end-use demands are scaled from urban demands within Edmonton. Data collection both by specific urban end uses and by regional water users would permit improved model calibration and validation. Additionally, the cost of policy implementation is an important consideration for decision makers in water resource management and is expected to affect the choices and behaviors of water users. More research is required in this area both for the Edmonton region and for other locations around the world. New research should explore possible water conservation policies and the degree to which citizens or customers respond to the application of water-saving policies. For example, because the implemented policies are all related to residential and multi-residential water demand and changes in ICI water demand are neglected, an investigation of the factors that affect ICI water demand would be useful for future research. The characteristics of industry, commerce and institutions in the Edmonton region in 2100 may differ significantly from current conditions with development of the municipality. Thus, separating the ICI sector as individual industrial, commercial and institutional sectors may prove important, and would allow users to explore alternative development routes of each individual end use and the value of specific end-use policies to conserve water.

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Appendix A. Code for Daily/Weekly demand Forecasting User Interface

Three files required for user interface development in R are provided below to aid model reproduction.

(1) Code in "server.R" file

```
## Load information of optimum ANNs
source("global.R")
## Required Packages
library(neuralnet)
library(RgoogleMaps)
library(rlang)
library(caret)
library(MASS)
library(neuralnet)
library(ELMR)
library(plyr)
library(dplyr)
library(randomForest)
library(psych)
library(stats)
library(hydroGOF)
library(htmlwidgets)
library(DT)
source("findhidbest.R")
## Initial Setting
k.proportion = 0.7
options(digits=4)

## Server
```

```
server <- function(input, output, session) {

 ## Weekly/Daily Selection
  t <- reactive({
    if( is.null(input$type)){
      NA
    }
    else {type <- switch(input$type,weekly = 1, daily = 2,quoted = TRUE)
    }})

   t2 <- reactive({
    if( is.null(input$time)){
      NA
    }
    else {time <- switch(input$time,weekly = 1, daily = 2,quoted = TRUE)
    }})

 ## Model Selection
  m <- reactive({
    if( is.null(input$type)){
      NA
    }
    else {if(t() == 1){
      ann <-  switch (input$ann,
                      bpnn = Sim.nn.w,
                      elm = Sim.elm.w)
    }
      else{
        ann <-  switch (input$ann,
                        bpnn = Sim.nn.d,
                        elm = Sim.elm.d)}}
  })
```

```
## Data Near the Selected Date
output$ac <- DT::renderDataTable(
   if (t2() == 2){
    for(i in 1:nrow(weather.all)){
     if(identical(as.character(weather.all[i,1]),(str_sub(as.character(input$date), -2))))
     { q <- i}}
    ac <- weather.all[(q-5):q,]
    ac2<-ac[,c(1,2,3,4,6,5)]}
  else{if (t2() == 1){
   ac <- forecastw
  ac2 <- ac[,c(1,2,3,4,6,5)]}},
  rownames= FALSE,options = list(dom = 't',ordering=F)
)
```

Hints of Required Model Inputs

```
output$hint<-renderUI({
  when <- input$when
  Index <- reactive(input$index)
   if(identical(m(), Sim.nn.w)){
    HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>","Mean
Temp.[t],  Mean Temp.[t-1]", " Amount of P[t],  Amount of P[t-1]",  "Water Demand[t-
1]","<br/><br/>",sep = "<br/><br/>"))  }
   else{if(identical(m(), Sim.elm.w)){
    HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>", "Min
Temp.[t],  Min Temp.[t-1]",  "Max Temp.[t],  Max Temp.[t-1]",  "Mean Temp.[t],  Mean
Temp.[t-1]",  "Amount of P[t], Amount of P[t-1]",  "Water Demand[t-1]","<br/><br/>",sep =
"<br/><br/>")) }


  else{if(Index()==1){if(identical(m(), Sim.nn.d)){
   HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>", "Min
Temp.[t],  Min Temp.[t-2]", "Max Temp.[t],  Max Temp.[t-1]",  "Amount of P[t],  Amount of
P[t-1]",  "Occurrence of P[t-5]",  "Water Demand[t-1],  Water Demand[t-2]","<br/><br/>",sep =
"<br/><br/>")) }


     else{if(identical(m(), Sim.elm.d)){
```

```
          HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>", "Min
Temp.[t],  Min Temp.[t-2]",  "Max Temp.[t],  Max Temp.[t-1]",  "Amount of P[t],  Amount of
P[t-1]", " Occurrence of P[t-4]",  "Water Demand[t-1],  Water Demand[t-2] ","<br/><br/>",sep =
"<br/><br/>")) }}}


   else{if(Index()==0){
          if(identical(m(), Sim.nn.d)){
            HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>", " Min
Temp.[t],  Min Temp.[t-2]",  "Max Temp.[t],  Max Temp.[t-1]",  "Amount of P[t], Amount of
P[t-1]",  "Occurrence of P[t-1]",  "Water Demand[t-1],  Water Demand[t-2]","<br/><br/>",sep =
"<br/><br/>")) }


          else{if(identical(m(), Sim.elm.d)){
            HTML(paste(icon("info-circle"),"<b>Please fill below inputs on the right:<b>", "Min
Temp.[t],  Min Temp.[t-2]",  "Max Temp.[t],  Max Temp.[t-1]",  "Amount of P[t],  Amount of
P[t-1]",  "Occurrence of P[t]", " Water Demand[t-1],  Water Demand[t-2] ","<br/><br/>",sep =
"<br/><br/>")) }}}
  }}}})
```

Prediction Results (Tab 1)

```
  output$resultrecent<- DT::renderDataTable(


   if(t2()==1){
    pastdemand <- reactive(input$pastdemand)
    if(is.na(pastdemand()))
    { WaterDemand <- NA
    Type <- "BPNN"
    WaterDemand.nn <- as.data.frame(cbind(Type,nw[1],WaterDemand))
    colnames(WaterDemand.nn)<-c("Model","Date","Water Demand")
    WaterDemand.nn
        }
    else{
      or.w.nn <- cbind(pastdemand(),or.w.nn)
      for (i in 1:ncol(or.w.nn)) {
        or.w.nn[1,i] <-(or.w.nn[1,i]-min(or.data1[,i+1]))/(max(or.data1[,i+1])-
min(or.data1[,i+1]))}
```

```
    WaterDemand<-
round(as.numeric((neuralnet::compute(nn.w,or.w.nn))$net.result)*(max(or.data1$D)-
min(or.data1$D))+min(or.data1$D),2)
    Type <- "BPNN"
    WaterDemand.nn<-as.data.frame(cbind(Type,nw[1],WaterDemand))
    colnames(WaterDemand.nn)<-c("Model","Week","Water Demand")
    WaterDemand.nn
   }}
  else{if(t2()==2){
   pastdemand <- reactive(input$pastdemand)
   pastdemanda <- reactive(input$pastdemanda)
   for(i in 1:nrow(weather.all)){
    if(identical(as.character(weather.all[i,1]),(str_sub(as.character(input$date), -2))))
    { q <- i}}
   abc <- weather.all[(q-5):(q),]
   or.d.nn <-  cbind(abc[6,2],abc[4,2],abc[6,3],abc[5,3],abc[6,6],abc[5,6],abc[1,5])
   or.d.elm <- cbind(abc[6,2],abc[4,2],abc[6,3],abc[5,3],abc[6,6],abc[5,6],abc[2,5])
   options(lubridate.week.start=1)
   weekindex <- lubridate::wday(input$date)
   monthindex <- mday(input$date)
   if(is.na(pastdemand())|is.na(pastdemanda()))
   { WaterDemand <- NA
   Type <- "BPNN"
   WaterDemand.nn <- as.data.frame(cbind(Type,abc[6,1],WaterDemand))
   colnames(WaterDemand.nn)<-c("Model","Date","Water Demand")
   WaterDemand.nn
    }
   else{
    or.d.nn <- cbind(pastdemand(),pastdemanda(),or.d.nn,weekindex,monthindex)
    colnames(or.d.nn) <- names(or.data4[,-1])
    for (i in 1:ncol(or.d.nn)) {
     or.d.nn[1,i] <-(or.d.nn[1,i]-min(or.data4[,i+1]))/(max(or.data4[,i+1])-min(or.data4[,i+1]))}
```

```
        WaterDemand<-
round(as.numeric((neuralnet::compute(nn.d,or.d.nn))$net.result)*(max(or.data4$D)-
min(or.data4$D))+min(or.data4$D),2)
        Type <- "BPNN"
        WaterDemand.nn<-as.data.frame(cbind(Type,abc[6,1],WaterDemand))
        colnames(WaterDemand.nn)<-c("Model","Date","Water Demand")
        WaterDemand.nn
))
   }
   }},
   rownames= FALSE,options = list(dom = 't',ordering=F))


  ## Prediction Results (Tab 2)
  tmean <- reactive(input$tmean)
  tmean_1 <- reactive(input$tmean_1)
  p <- reactive(input$p)
  p_1 <- reactive(input$p_1)
  pastdemand1 <- reactive(input$pastdemand1)
  tmax <- reactive(input$tmax)
  tmax_1 <- reactive(input$tmax_1)
  tmin <- reactive(input$tmin)
  tmin_1 <- reactive(input$tmin_1)
  pastdemand2 <- reactive(input$pastdemand2)
  tmin_2 <- reactive(input$tmin_2)
  op <-  reactive(input$op)
  op_1 <-  reactive(input$op_1)
  op_2 <-  reactive(input$op_2)
  op_4 <-  reactive(input$op_4)
  op_5 <-  reactive(input$op_5)
  Weekindex <- reactive(input$weekindex)
  Monthindex <- reactive(input$monthindex)
  Index <- reactive(input$index)
```

```
output$resultplay <- DT::renderDataTable(

  if(identical(m(), Sim.nn.w)){
    or.w.nn <-as.data.frame(cbind(pastdemand1(),tmean(),tmean_1(),p(),p_1()))
    for (i in 1:ncol(or.w.nn)) {
      or.w.nn[1,i] <-(or.w.nn[1,i]-min(or.data1[,i+1]))/(max(or.data1[,i+1])-min(or.data1[,i+1]))
    }
    WaterDemand<-
round(as.numeric((neuralnet::compute(nn.w,or.w.nn))$net.result)*(max(or.data1$D)-
min(or.data1$D))+min(or.data1$D),2)
    Model <- "BPNN"
    WaterDemand<-as.data.frame(cbind(Model,"Unknown",WaterDemand))
    colnames(WaterDemand)<-c("Model","Week","Water Demand")
    WaterDemand
  }
  else{if(identical(m(), Sim.elm.w)){
        or.w.elm<-
as.data.frame(cbind(pastdemand1(),pastdemand1(),tmax(),tmax_1(),tmin(),tmin_1(),tmean(),tme
an_1(),p(),p_1()))


if(is.na(pastdemand1())|is.na(tmax())|is.na(tmax_1())|is.na(tmin())|is.na(tmin_1())|is.na(tmean())|i
s.na(tmean_1())|is.na(p())|is.na(p_1()))
    { WaterDemand <- NA
    Model <- "ELM"
    WaterDemand <- as.data.frame(cbind(Model,"Unknown",WaterDemand))
    colnames(WaterDemand)<-c("Model","Week","Water Demand")
    WaterDemand
    }
    else{
      for (i in 1:ncol(or.w.elm)) {
        or.w.elm[1,i] <-(or.w.elm[1,i]-min(or.data2[,i]))/(max(or.data2[,i])-min(or.data2[,i]))
      }
      colnames(or.w.elm) <- names(or.data2)
```

```
      WaterDemand <-
round(as.numeric((predict_elm(elm.w,or.w.elm))$predicted)*(max(or.data2$D)-
min(or.data2$D))+min(or.data2$D),2)
      Model <- "ELM"
      WaterDemand <- as.data.frame(cbind(Model,"Unknown",WaterDemand))
      colnames(WaterDemand)<-c("Model","Week","Water Demand")
      WaterDemand}
  }

   else{if(Index()==1){
    if(identical(m(), Sim.nn.d)){
      or.d.nn<-
cbind(pastdemand1(),pastdemand2(),tmin(),tmin_2(),tmax(),tmax_1(),p(),p_1(),op_5(),Weekind
ex(),Monthindex())
      for (i in 1:ncol(or.d.nn)) {
        or.d.nn[1,i] <-(or.d.nn[1,i]-min(or.data4[,i+1]))/(max(or.data4[,i+1])-min(or.data4[,i+1]))
      }
      WaterDemand<-
round(as.numeric(neuralnet::compute(nn.d,or.d.nn)$net.result)*(max(or.data4$D)-
min(or.data4$D))+min(or.data4$D),2)
      Model <- "BPNN"
      WaterDemand<-as.data.frame(cbind(Model,"Unknown",WaterDemand))
      colnames(WaterDemand)<-c("Model","Date","Water Demand")
      WaterDemand}
      else{if(identical(m(), Sim.elm.d)){

if(is.na(pastdemand1())|is.na(pastdemand2())|is.na(tmin())|is.na(tmin_2())|is.na(tmax())|is.na(tma
x_1())|is.na(p())|is.na(p_1())|is.na(op_4()))
        {WaterDemand <- NA
        Model <- "ELM"
        WaterDemand <- as.data.frame(cbind(Model,"Unknown",WaterDemand))
        colnames(WaterDemand)<-c("Model","Date","Water Demand")
        WaterDemand
        }
        else{
```

```
          or.d.elm<-
as.data.frame(cbind(pastdemand1(),pastdemand1(),pastdemand2(),tmin(),tmin_2(),tmax(),tmax_
1(),p(),p_1(),op_4(),Weekindex(),Monthindex()))
          for (i in 1:ncol(or.d.elm)) {
            or.d.elm[1,i] <-(or.d.elm[1,i]-min(or.data3[,i]))/(max(or.data3[,i])-min(or.data3[,i]))
          }
          colnames(or.d.elm)<-names(or.data3)
          WaterDemand<-
round(as.numeric((predict_elm(elm.d,or.d.elm))$predicted)*(max(or.data3$D)-
min(or.data3$D))+min(or.data3$D),2)
          Model <- "ELM"
          WaterDemand<-as.data.frame(cbind(Model,"Unknown",WaterDemand))
          colnames(WaterDemand)<-c("Model","Date","Water Demand")
          WaterDemand}
      }}}

   else{if(Index()==0){
      if(identical(m(), Sim.nn.d)){
        or.d.nn <-
cbind(pastdemand1(),pastdemand2(),tmin(),tmin_2(),tmax(),tmax_1(),p(),p_1(),op_1())
        for (i in 1:ncol(or.d.nn)) {
          or.d.nn[1,i] <-(or.d.nn[1,i]-min(or.data6[,i+1]))/(max(or.data6[,i+1])-min(or.data6[,i+1]))
        }
        WaterDemand<-
round(as.numeric((neuralnet::compute(nn.di,or.d.nn))$net.result)*(max(or.data6$D)-
min(or.data6$D))+min(or.data6$D),2)
        Model <- "BPNN"
        WaterDemand<-as.data.frame(cbind(Model,"Unknown",WaterDemand))
        colnames(WaterDemand)<-c("Model","Date","Water Demand")
        WaterDemand
      }
        else{if(identical(m(), Sim.elm.d)){

if(is.na(pastdemand1())|is.na(pastdemand2())|is.na(tmin())|is.na(tmin_2())|is.na(tmax())|is.na(tma
x_1())|is.na(p())|is.na(p_1())|is.na(op()))
```

```
{ WaterDemand <- NA
Model <- "ELM"
WaterDemand <- as.data.frame(cbind(Model,"Unknown",WaterDemand))
colnames(WaterDemand)<-c("Model","Date","Water Demand")
WaterDemand
}
else{
 or.d.elm<-
as.data.frame(cbind(pastdemand1(),pastdemand1(),pastdemand2(),tmin(),tmin_2(),tmax(),tmax_
1(),p(),p_1(),op()))
 for (i in 1:ncol(or.d.elm)) {
  or.d.elm[1,i] <-(or.d.elm[1,i]-min(or.data5[,i]))/(max(or.data5[,i])-min(or.data5[,i]))
 }
 colnames(or.d.elm)<-names(or.data5)
 WaterDemand <-
round(as.numeric((predict_elm(elm.di,or.d.elm))$predicted)*(max(or.data5$D)-
min(or.data5$D))+min(or.data5$D),2)
 Model <- "ELM"
 WaterDemand<-as.data.frame(cbind(Model,"Unknown",WaterDemand))
 colnames(WaterDemand)<-c("Model","Date","Water Demand")
 WaterDemand}
}}}}}},
rownames= FALSE,options = list(dom = 't',ordering=F)
)
output$pdfview <- renderUI({
  tags$iframe(style="height:700px; width:100%", src="definitions.pdf") })
}
```

(2) Code in “ui.R” file

```
# Required Packages
library(shiny)
library(shinydashboard)
library(gcookbook)
library(grid)
library(leaflet)
library(shinyalert)
library(shinythemes)
## User Interface
ui<- navbarPage(HTML("<b>EPCOR Water Demand Forecasting"),theme =
shinytheme("flatly"),
                    tabPanel("[ Prediction -- Automatic ]",box(width = 14,title= "",solidHeader =
TRUE, status = "primary", sidebarLayout(
                    sidebarPanel(width=3,radioButtons("time",label = list( icon("clock"), "Simulation
Period:"), c("Daily" = "daily","Weekly" = "weekly" ),selected = "daily"), br(), br(),
                    dateInput("date", label = span(tagList( icon("calendar"), "Choose from
Calendar:")), value = current, min = current-14, max = current+14, format = "yyyy-mm-dd"),
br(),
                    numericInput(value = NULL,"pastdemand", label = list(icon("tint"), "Water
Demand[Yesterday / Last week]")), br(),
                    numericInput(value = NULL,"pastdemanda", label = list(icon("tint"),"Water
Demand [The day before yesterday]")),br(),br()),
                    mainPanel(column(width=12, box(title = "Weather Data", width=12,
DT::dataTableOutput("ac")),box(title="",width=12,height=10),box(title = "Predicted Demand",
status = "primary", solidHeader = TRUE, DT::dataTableOutput( "resultrecent"))))))),


                    tabPanel("[ Prediction -- Manual ]",sidebarLayout(sidebarPanel(width=3,
                    radioButtons("type", label = list( icon("clock"), "Simulation Period:"), c("Daily"
        = "daily", "Weekly" = "weekly"), inline= TRUE), br(),
                    radioButtons("ann", label = list( icon("mouse-pointer"), "Model Selection:"),
        c("BPNN" = "bpnn","ELM" = "elm"), inline= TRUE), br(),
```

```
radioButtons("index", label = list( icon("sort-numeric-up"),"Index? :"),c("Yes" =
1,"No" = 0),inline= TRUE), htmlOutput(outputId = "hint")),
mainPanel(box(width=20,title= "Required Inputs",splitLayout( column(width =
12,
numericInput("tmin",value = NA, width = 150,label="Min Temp. [t]"),
numericInput("tmin_1",value = NA, width = 150, label = "Min Temp. [t-1]"),
numericInput("tmin_2",value = NA, width = 150, label = "Min Temp. [t-2]")),
column(width = 12,
numericInput("tmax",value = NA, width = 150, label = "Max Temp. [t]"),
numericInput("tmax_1",value = NA, width = 150, label = "Max Temp. [t-1]"),
numericInput("tmax_2",value = NA, width = 150, label = "Max Temp. [t-2]")),
column(width = 12,
numericInput("tmean",value = NA, width = 150, label = "Mean Temp. [t]"),
numericInput("tmean_1",value = NA, width = 150, label = "Mean Temp. [t-1]"),
numericInput("tmean_2",value = NA, width = 150, label = "Mean Temp. [t-
2]")),
column(width = 12,
numericInput("p",value = NA, width = 150, label = "Amount of P [t]"),
numericInput("p_1",value = NA, width = 150, label = "Amount of P [t-1]"),
numericInput("p_2",value = NA, width = 150, label = "Amount of P[t-2]")),
column(width = 12,
numericInput("op",value = NA, width = 150, label = "Occurrence of P[t]"),
numericInput("op_1",value = NA, width = 150, label = "Occurrence of P[t-1]"),
numericInput("op_2",value = NA, width = 150, label = "Occurrence of P[t-2]"),
numericInput("op_4",value = NA, width = 150, label = "Occurrence of P[t-4]"),
numericInput("op_5",value = NA, width = 150, label = "Occurrence of P[t-5]")),
column(width = 12,
numericInput("pastdemand1",value = NA, width = 150, label = "Water
Demand[t-1]"),
numericInput("pastdemand2",value = NA, width = 150, label = "Water
Demand[t-2]"),
```

```
numericInput("weekindex",value = NA, width = 150, label = "'Day-in-Week'
Index"),
numericInput("monthindex",value = NA, width = 150, label = "'Day-in-Month'
Index")))),
box(width = 14,inputId = "resultplay",title = "Predicted Demand", status =
"primary", solidHeader = TRUE,DT::dataTableOutput("resultplay")) ))),
("   [ Readme ]",tabPanel(solidHeader = TRUE,"README",box(width = 14,
title= "",solidHeader = TRUE, status = "primary", uiOutput("pdfview")))))
```

(3) Code in "global.R" file

```
load("Model workspace2.RData")
## Requires Packages
library(XML)
library(RCurl)
library(rvest)
library(xml2)
library(stringr)
library(lubridate)
library(data.table)
library(tidyverse)
library(htmltools)
current <- Sys.Date()
c <- as.data.frame(strsplit(as.character(current), "-"))
m <- as.numeric(as.character(c[2,1]))
d <- as.character(c[3,1])
y <- year(current)
w <- as.character(lubridate::wday(current,label = TRUE))

## Weather Forecasting
u<-
read_html(  "https://www.myforecast.com/index.php?cwid=gn5946768&metric=true&city_count
=2&zip_code=#forecast-15day")
u1 <-as.data.frame(html_nodes(u,"article.forecast-pod")%>%html_text("div"),stringsAsFactors =
FALSE)


for (i in 1:nrow(u1)) {
  if(is.null(u1[i,1])){u1[i,1] <- NA}
  u1[i,1] <-str_replace_all(u1[i,1],"\n","")
  u1[i,1] <-str_replace_all(u1[i,1]," ","")
```

```
}
u1<- na.omit(u1)
u2 <- data.frame()
for (i in 1:nrow(u1)) {
if(identical(substr(u1[i,1],1,3),"Mon")|identical(substr(u1[i,1],1,3),"Tue")|identical(substr(u1[i,1]
,1,3),"Wed")|identical(substr(u1[i,1],1,3),"Thu")|identical(substr(u1[i,1],1,3),"Fri")|identical(subs
tr(u1[i,1],1, 3),"Sat")|identical(substr(u1[i,1],1, 3),"Sun"))
u2[i,1]<-u1[i,1]}
u3 <- u2[1,]
u2 <- as.data.frame(na.omit(u2[-c(1:8),]),stringsAsFactors = FALSE)
u2 <- u2[c(1:15),]
udate <- str_split_fixed(u2,"\t\t\t\t",2)[,1]
utemp <- str_split_fixed(str_split_fixed(u2,"\t\t\t\t",2)[,2],"\u00B0",3)[,1:2]
utemp <- utemp[,c(2,1)]
uweekday <- str_sub(udate,end = 3)
udate <- str_sub(udate,4,5)


u<-
read_html("https://www.myforecast.com/index.php?cwid=gn5946768&metric=false&city_count
=2&zip_code=#forecast-15day")
udetail<-as.data.frame(html_nodes(u,"div.forecast-
detail")%>%html_text("div"),stringsAsFactors = FALSE)
for (i in 1:nrow(udetail)) {
  udetail[i,1] <- str_replace_all(udetail[i,1],"\n","")
  udetail[i,1] <- str_replace_all(udetail[i,1]," ","")
}


up <- str_split_fixed(udetail[,1], "UVIndex", 2)[1:15,2]
uop <- str_split_fixed(up, "Precip.%", 2)[1:15,1]
uap <- str_sub(str_split_fixed(up, "Precip.%", 2)[1:15,2],end = -19)
```

```
tf <- as.data.frame(cbind(uweekday,udate,utemp,uop,uap))
colnames(tf)<-c("Weekday","Date","Min temp(`C)","Max temp(`C)","chance of precip(%)","Amount of Precip(mm)")

tf[,1] <- as.data.frame(tf[,1])
tf[,3] <- as.numeric(as.character(tf[,3]))
tf[,4] <- as.numeric(as.character(tf[,4]))
tf[,5] <- as.numeric(as.character(sub('.$','',tf[,5])))
tf[,6] <- as.numeric(as.character(tf[,6]))*25.4

for(i in 1:nrow(tf)){
  if (is.na(tf[i,6]))
  {tf[i,6]=0}}
colnames(tf)<-c("Weekday","Date","Min temp(`C)","Max temp(`C)","chance of precip(%)","Amount of Precip(mm)")

tf2 <- tf[,-1]
tf2[,6] <- tf2[,5]
for (i in 1:nrow(tf2)) {
  if(tf2[i,5]==0){tf2[i,5]=0}else{tf2[i,5]=1}
  tf2[i,4] <- (tf2[i,2]+tf2[i,3])/2
}
colnames(tf2)<- c("Date","Min temp(`C)","Max temp(`C)","Mean temp(`C)","occurrence of precip","Amount of Precip(mm)")
o <- as.character(tf2[,1])
for (i in 1:length(o)) {
  o[i]=paste(rep(0,2-nchar(o[i])),o[i],sep="")
}
tf2$Date <- o
```

Weather Record

```
yest <- current-1
c <- as.data.frame(strsplit(as.character(yest), "-"))
m_1 <- as.numeric(as.character(c[2,1]))
d_1 <- as.character(c[3,1])
y2 <- year(yest)
if (m < 10){
  m_= paste(rep(0,2-nchar(as.numeric(m))),as.numeric(m),sep="")
}else{m_=m}

if (m == 1){
  m2 <- 12
  y2 <- y-1
}else{y2 <- y
if (m > 10){
  m2 <- m-1
}else{m2 <- paste(rep(0,2-nchar(m-1)),m-1,sep="")}}

url<-read_html(paste(sep=
"","http://climate.weather.gc.ca/climate_data/daily_data_e.html?hlyRange=1999-06-
23%7C",y,"-",m_,"-",d,"&dlyRange=1996-03-01%7C",y,"-",m_,"-",d,"&mlyRange=1996-03-
01%7C2007-11-
01&StationID=27214&Prov=AB&urlExtension=_e.html&searchType=stnName&optLimit=year
Range&StartYear=1840&EndYear=",y,"&selRowPerPage=25&Line=",d,"&searchMethod=cont
ains&Month=",m_,"&Day=",d,"&txtStationName=edmonton&timeframe=1&Year=",y,"#"))
url <-html_table(url)
ta<-url[[1]]
ta<-ta[1:(nrow(ta)-4),]
url2<-read_html(paste(sep=
"","http://climate.weather.gc.ca/climate_data/daily_data_e.html?hlyRange=1999-06-
23%7C",y2,"-",m2,"-",d_1,"&dlyRange=1996-03-01%7C",y2,"-",m2,"-
",d_1,"&mlyRange=1996-03-01%7C2007-11-
```

```
01&StationID=27214&Prov=AB&urlExtension=_e.html&searchType=stnName&optLimit=yearRange&StartYear=1840&EndYear=",y2,"&selRowPerPage=25&Line=",d_1,"&searchMethod=contains&Month=",m2,"&Day=",d_1,"&txtStationName=edmonton&timeframe=1&Year=",y2,"#"))
url2 <-html_table(url2)
ta2 <-url2[[1]]
if(m2 == 2|m2==4|m2==6|m2==9|m2==11){ta2 <- ta2[1:(nrow(ta2)-5),]
}else{ta2 <- ta2[1:(nrow(ta2)-4),]}
if(identical(ta,ta2)==FALSE){ta <- rbind(ta2,ta)}else{ta <- ta}

if(as.numeric(as.character(ta[nrow(ta),1]))== d){ta <- ta[-nrow(ta),]}
tp<-cbind(ta[,1:4],suppressWarnings(as.numeric(as.character(ta[,9]))))
tp[,2] <- as.numeric(as.character(ta[,3]))
tp[,3] <- as.numeric(as.character(ta[,2]))
tp[,4] <- as.numeric(as.character(tp[,4]))
tp[,6] <- as.numeric(as.character(tp[,5]))
for(i in  1:nrow(tp)){
  if (identical(tp[i,6],0))
  {tp[i,5]=0}
  else{tp[i,5] = 1}}
colnames(tp)<- c("Date","Min temp(`C)","Max temp(`C)","Mean temp(`C)","occurrence of precip","Amount of Precip(mm)")
```

Missing Data Replacement

```
datemissing.all <- NULL
datemissing <- NULL
for (i in 1:nrow(tp)){
  for (k in 1:ncol(tp))
    if (is.na(tp[i,k])){
      datemissing <- i
    }
```

```
  datemissing.all <-rbind(datemissing.all,datemissing)
}
datemissing.all <- datemissing.all[!duplicated(datemissing.all[,1], fromLast=TRUE),]

if (is.null(datemissing.all[1])==FALSE){
  miss<-read_html(paste(sep=
"","http://climate.weather.gc.ca/climate_data/daily_data_e.html?hlyRange=1999-06-
23%7C",y,"-",m_,"-",d_1,"&dlyRange=1996-03-01%7C",y,"-",m_,"-",d_1,"&mlyRange=1996-
03-01%7C2007-11-
01&StationID=53718&Prov=AB&urlExtension=_e.html&searchType=stnName&optLimit=year
Range&StartYear=1840&EndYear=",y,"&selRowPerPage=25&Line=",d_1,"&searchMethod=co
ntains&Month=",m_,"&Day=",d_1,"&txtStationName=edmonton&timeframe=1&Year=",y,"#"))
  miss <-html_table(miss)
  mta<-miss[[1]]
  mta<-mta[1:(nrow(mta)-4),]

# if( as.numeric(d)<31){murl2<-
read_html(paste(sep="","http://climate.weather.gc.ca/climate_data/daily_data_e.html?hlyRange=
1999-06-23%7C",y2,"-",m2,"-",d_1,"&dlyRange=1996-03-01%7C",y2,"-",m2,"-
",d_1,"&mlyRange=1996-03-01%7C2007-11-
01&StationID=53718&Prov=AB&urlExtension=_e.html&searchType=stnName&optLimit=year
Range&StartYear=1840&EndYear=",y2,"&selRowPerPage=25&Line=",d_1,"&searchMethod=c
ontains&Month=",m2,"&Day=",d_1,"&txtStationName=edmonton&timeframe=1&Year=",y2,"#
"))
    murl2 <-html_table(murl2)
    mta2 <- murl2[[1]]
    if(m==2|m==4|m==6|m==9|m==11)
    {mta2 <- mta2[1:(nrow(mta2)-5),]
    }else{mta2 <- mta2[1:(nrow(mta2)-4),]}
    mta <- rbind(mta2,mta)
  #}else{mta <- mta}
```

```
  if(as.numeric(as.character(mta[nrow(mta),1]))== d){mta <- mta[-nrow(mta),]}
  mtp<-cbind(mta[,1:4],suppressWarnings(as.numeric(as.character(mta[,9]))))
  mtp[,2] <- as.numeric(as.character(mta[,3]))
  mtp[,3] <- as.numeric(as.character(mta[,2]))
  mtp[,4] <- as.numeric(as.character(mtp[,4]))
  mtp[,6] <- as.numeric(as.character(mtp[,5]))
  for(i in  1:nrow(mtp)){
    if (identical(mtp[i,6],0))
    {mtp[i,5]=0}
    else{mtp[i,5] = 1}}
  colnames(mtp)<- c("Date","Min temp(`C)","Max temp(`C)","Mean temp(`C)","occurrence of precip","Amount of Precip(mm)")
}

for (i in (datemissing.all)) {
  tp[i,] <-mtp[i,]
}
if (as.numeric(tp[nrow(tp),1])==as.numeric(d)){
  tp <- tp[-nrow(tp),]
}
weather.all <- rbind(tp,tf2)

## weekly data aggregation
lw<-as.data.frame(cbind(paste(tp[(nrow(tp)-6),1],"-",tp[nrow(tp),1]),min(tp[(nrow(tp)-6):nrow(tp),2]),max(tp[(nrow(tp)-6):nrow(tp),3]),mean(tp[(nrow(tp)-6):nrow(tp),4]),sum(tp[(nrow(tp)-6):nrow(tp),5]),sum(tp[(nrow(tp)-6):nrow(tp),6])))
colnames(lw)<- c("Week","Min temp(`C)","Max temp(`C)","Mean temp(`C)","occurrence of precip","Amount of Precip(mm)")
lw[,2] <- as.numeric(as.character(lw[,2]))
lw[,3] <- as.numeric(as.character(lw[,3]))
lw[,4] <- as.numeric(as.character(lw[,4]))
```

```
lw[,5] <- as.numeric(as.character(lw[,5]))

lw[,6] <- as.numeric(as.character(lw[,6]))

if(lw[1,5]==0){lw[1,5]=0}else{lw[1,5]=1}


nw<-as.data.frame(cbind(paste(tf2[1,1],"-
",tf2[7,1]),min(tf2[1:7,2]),max(tf2[1:7,3]),mean(tf2[1:7,4]),sum(tf2[1:7,5]),sum(tf2[1:7,6])))

colnames(nw)<- c("Week","Min temp(`C)","Max temp(`C)","Mean temp(`C)","occurrence of
precip","Amount of Precip(mm)")

nw[,2] <- as.numeric(as.character(nw[,2]))

nw[,3] <- as.numeric(as.character(nw[,3]))

nw[,5] <- as.numeric(as.character(nw[,5]))

nw[,6] <- as.numeric(as.character(nw[,6]))

nw[,4] <- as.numeric(as.character(nw[,4]))

if(nw[1,6]==0){lw[1,5]=0}else{nw[1,5]=1}

nw[,5] <- as.numeric(as.character(nw[,5]))
```

Result table Generation

```
forecastw <- rbind(lw,nw)

for(i in  1:nrow(tp)){

  if (identical(tp[i,6],0))

  {tp[i,5]=0}

  else{tp[i,5] = 1}}


forecastd <- rbind(tp[(nrow(tp)-1):nrow(tp),],tf2[1:2,])

times<-seq.Date(from = as.Date("1995-01-01",format = "%Y-%m-%d"), by = "day", length.out =
8613)

or.w.nn <- cbind(nw[1,4],lw[1,4],nw[1,6],lw[1,6])

or.w.elm <- cbind(nw[1,3],lw[1,3],nw[1,2],lw[1,2],nw[1,4],lw[1,4],nw[1,6],lw[1,6])
```

Appendix B. Code for Edmonton Water Demand Simulator (EWDS)

Code and sketch for EWDS are provided below to aid reproduction. Constant inputs are shown in green, changeable inputs are shown in orange, important outputs are shown in red, and shadow variables are shown in grey.

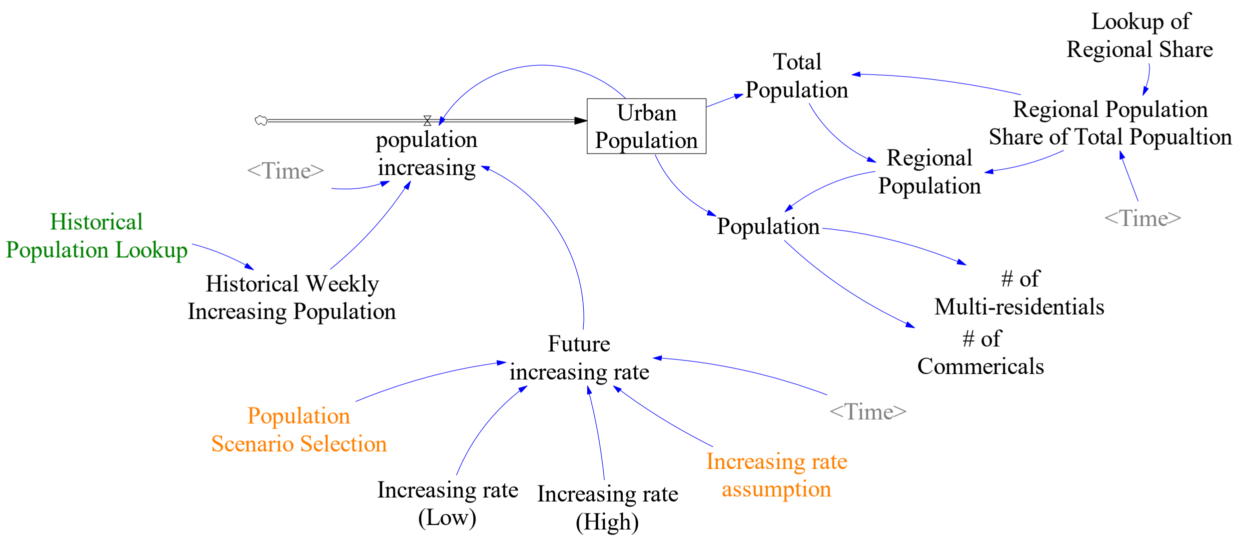

Fig. B-1 Population Simulation

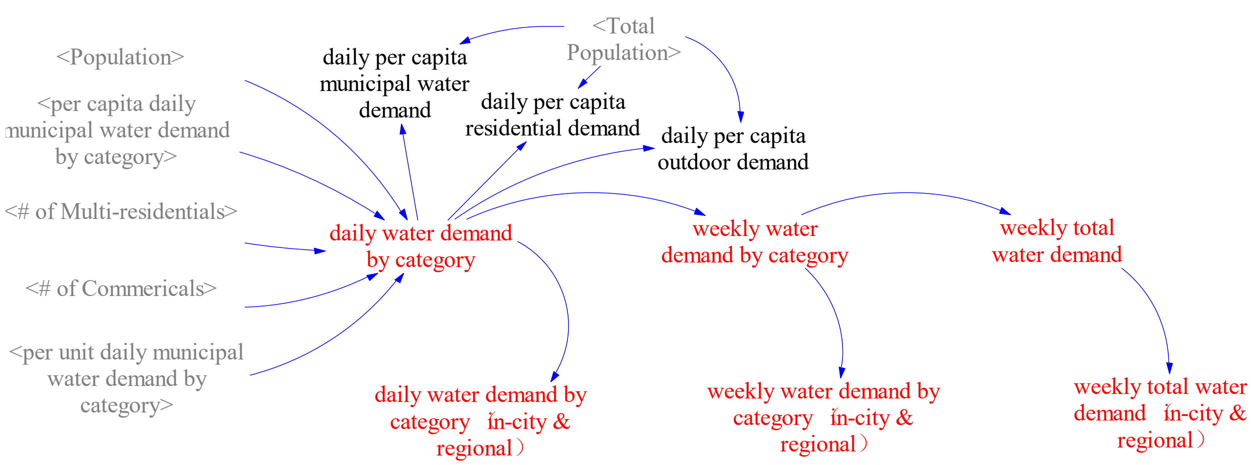

Fig. B-2 Total Water Demand Simulation

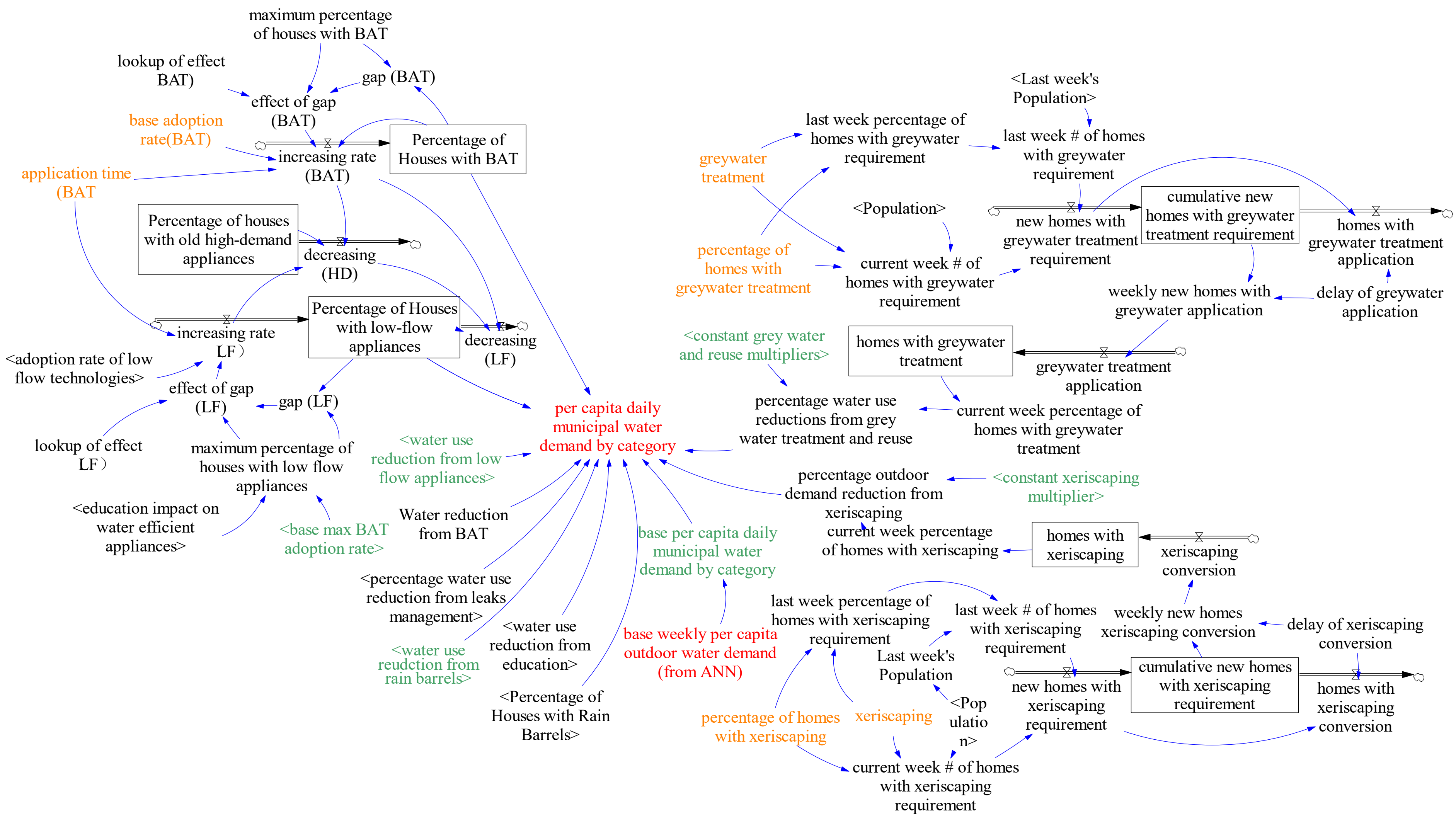

Fig. B-3 Policy Simulation

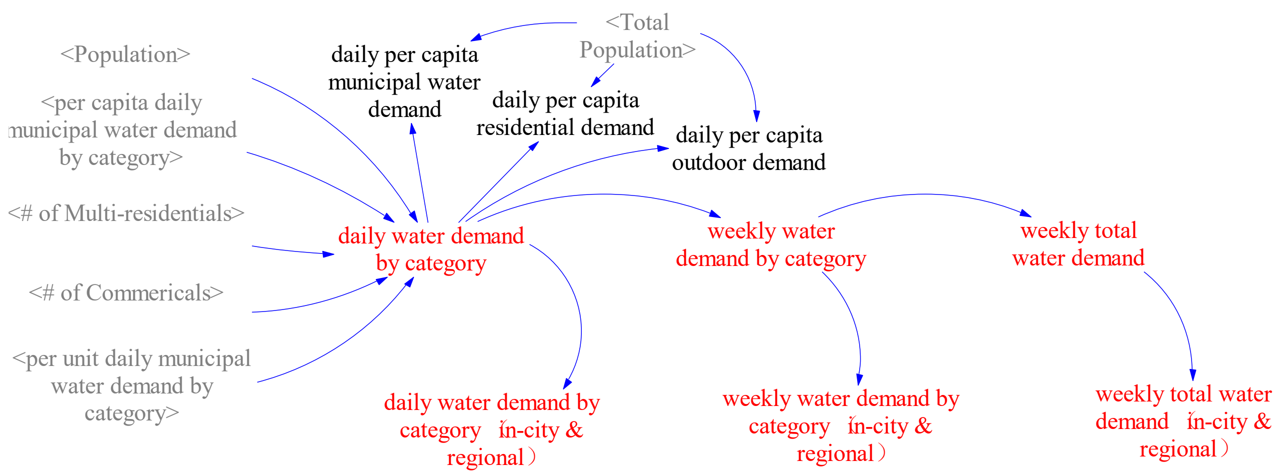

Fig. B-4 Total Water Demand Simulation

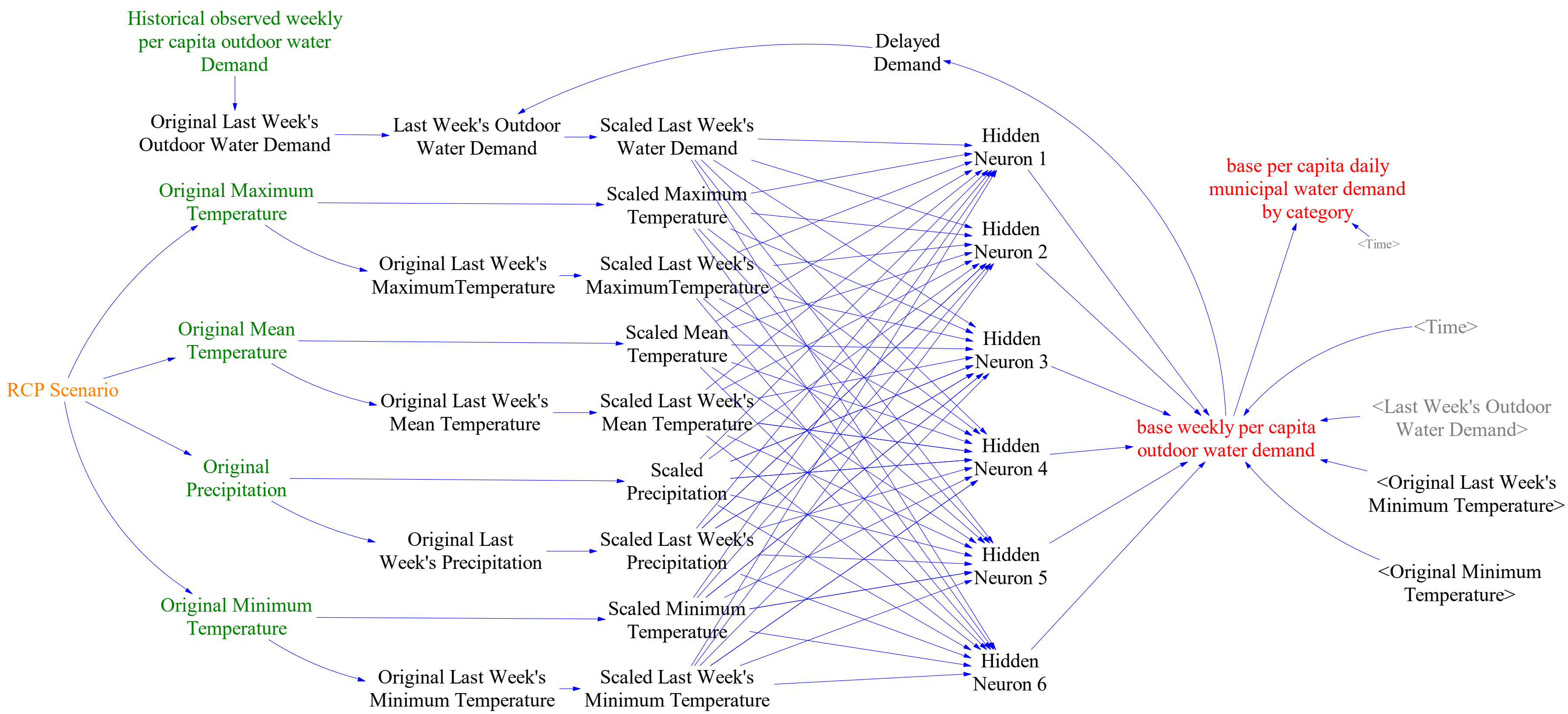

Fig. B-5 Outdoor Water Demand Simulation

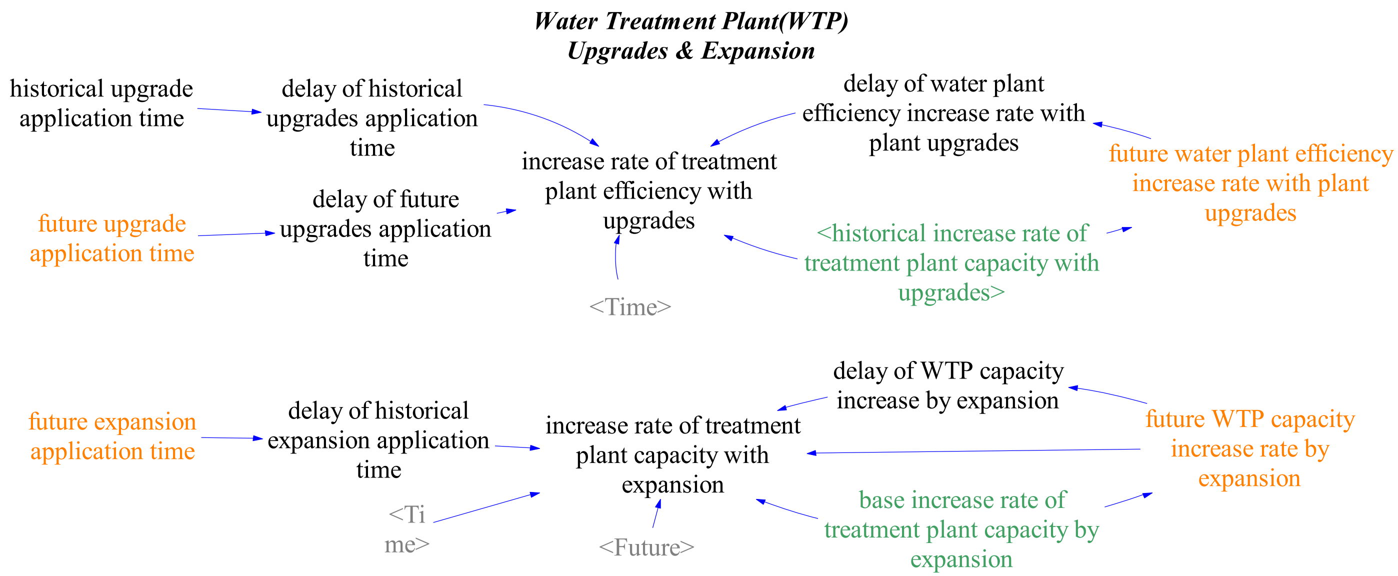

Fig. B-6 Water Treatment Plant (WTP) Upgrades & Expansion Simulation

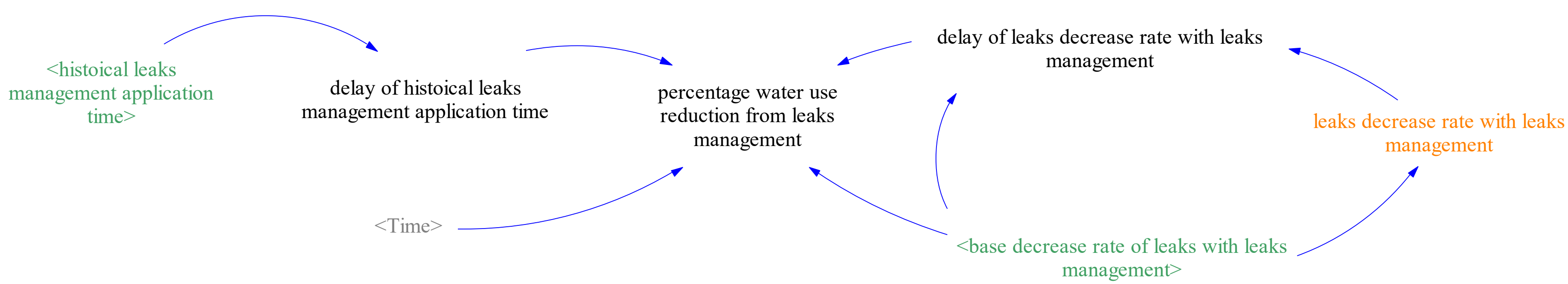

Fig. B-7 Leak Management Simulation

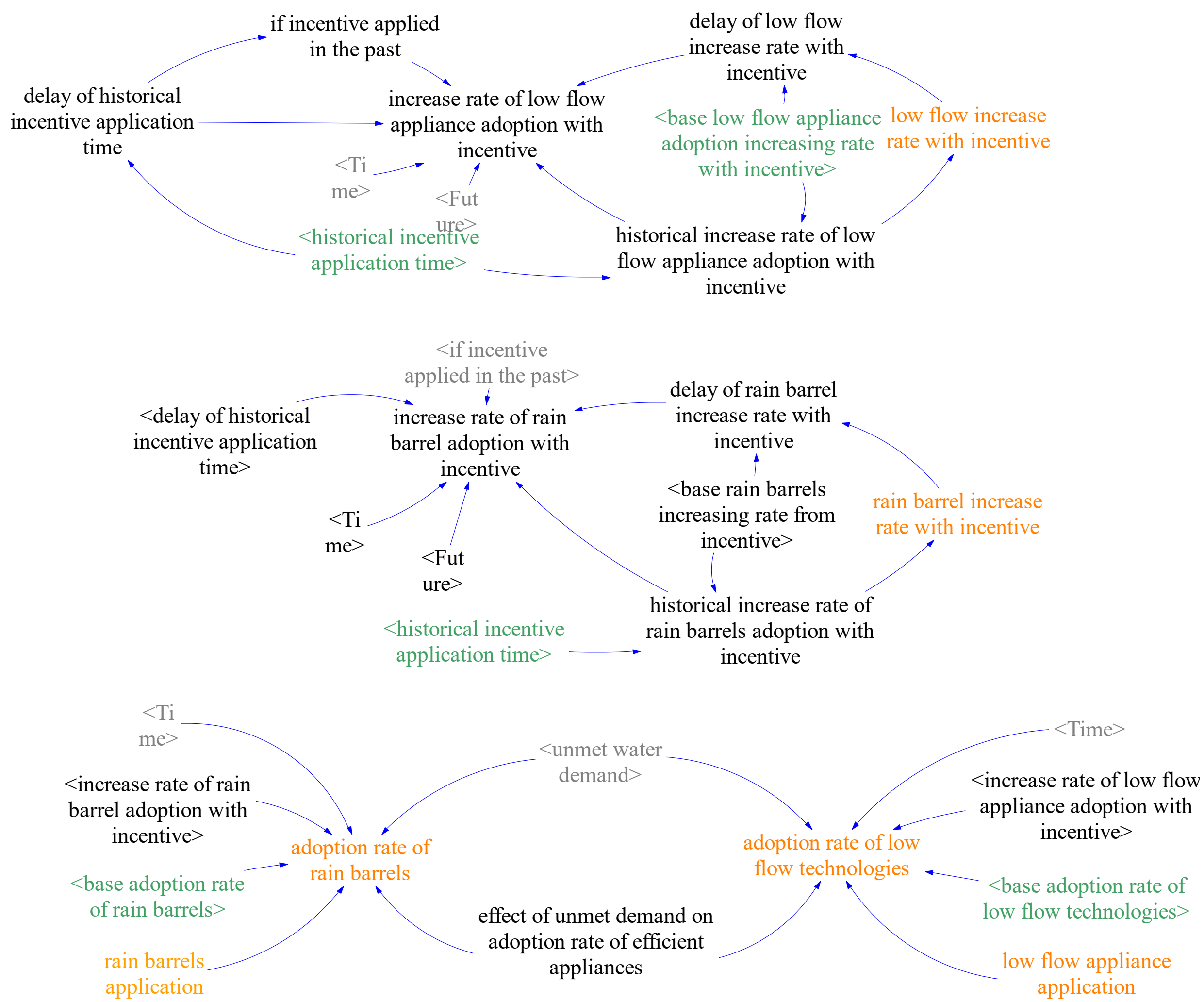

Fig. B-8 Economic incentive Simulation

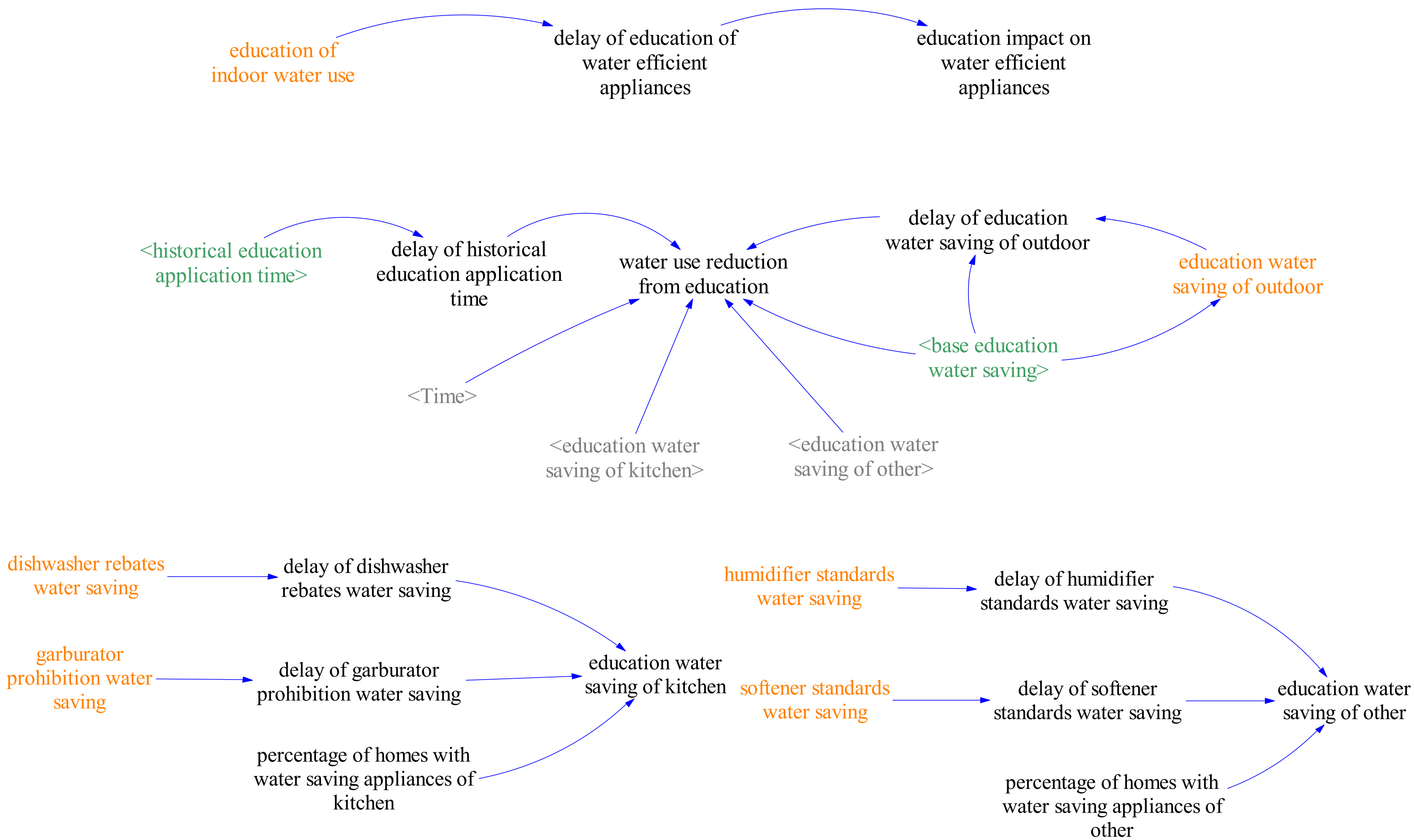

Fig. B-9 Education Simulation

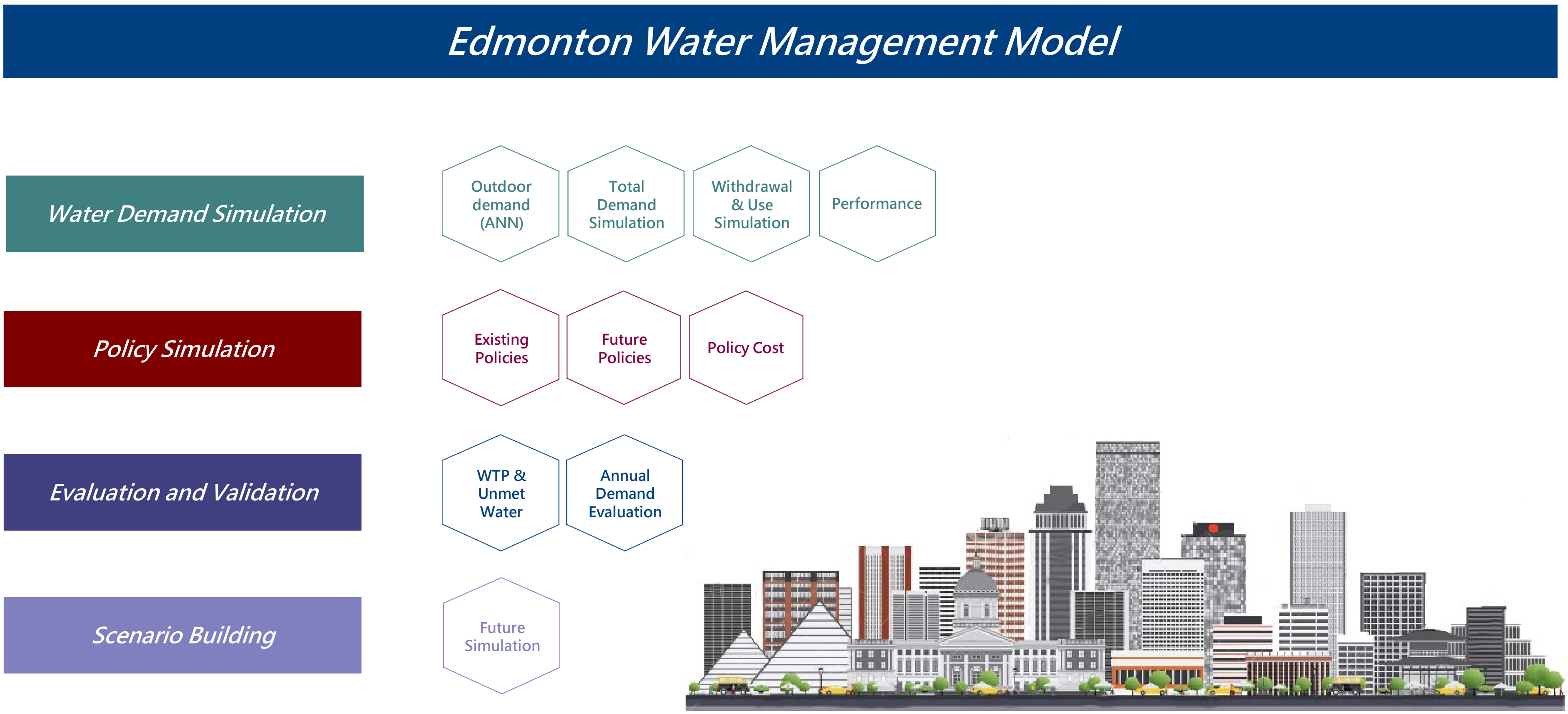

Fig. B-10 Homepage of EDWS

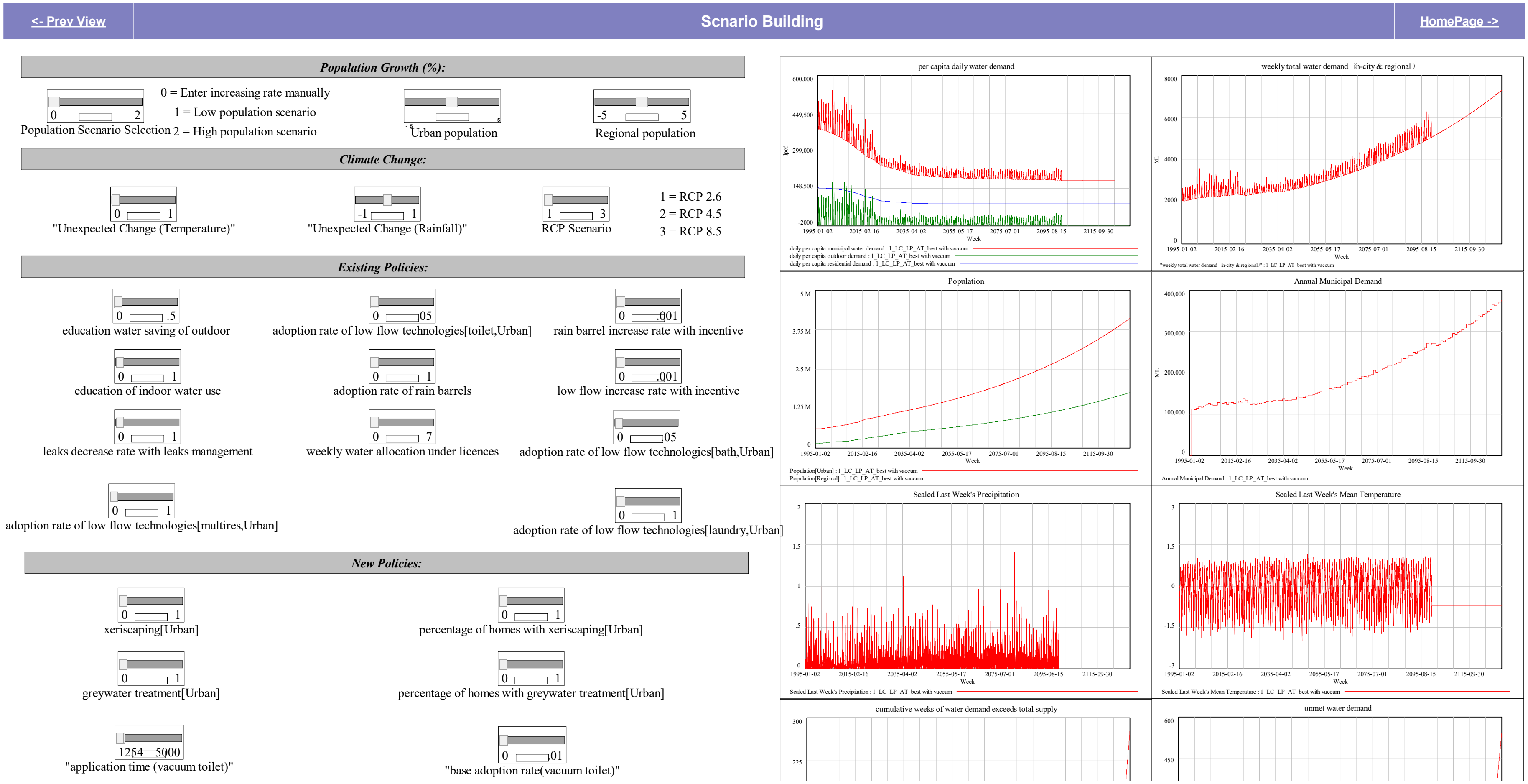

Fig. B-11 Scenario building interface of EDWS per unit daily municipal water demand by category[ici,Urban and Regional]=base per unit daily municipal water demand by category[ici,Urban and Regional]*((1-Percentage of Units with Low Flow Appliances[ici,Urban and Regional])*1+Percentage of Units with Low Flow Appliances[ici,Urban and Regional]*(1-water use reduction from low flow appliances[ici,Urban and Regional])), {UNIT: lpud}

per unit daily municipal water demand by category[multires,Urban and Regional]=base per unit daily municipal water demand by category[multires,Urban and Regional]*((1-Percentage of units with BATs[Urban and Regional]-Percentage of Units with Low Flow Appliances\[multires,Urban and Regional])*1+Percentage of Units with Low Flow Appliances[multires,Urban and Regional\]*(1-water use reduction from low flow appliances[multires,Urban and Regional])+Percentage of units with BATs[Urban and Regional]*(1-Water reduction from BAT[multires]))*(1-percentage water use reductions from grey water treatment and reuse[multires,Urban and Regional\])*(1-water use reduction from education[multires,Urban and Regional]), {UNIT: lpud}

"decreasing units (HF toilet)"[Urban and Regional]=IF THEN ELSE("Percentage of units with old high-flow toilet"[Urban and Regional]-increasing units rate （LF toilet\[Urban and Regional]-"increasing units rate (BAT)"[Urban and Regional]*0.12\<0, "Percentage of units with old high-flow toilet"[Urban and Regional],IF THEN ELSE("Percentage of units with old high-flow toilet"[Urban and Regional]=0, 0 , "increasing units rate (BAT)"[Urban and Regional]*0.12+increasing units rate（LF toilet）[Urban and Regional]))

increasing units rate （LF toilet）[Urban and Regional]=IF THEN ELSE(Time<"application time (BAT)"[Urban and Regional], low flow appliance change rate\[toilet,Urban and Regional],low flow appliance change rate[toilet,Urban and Regional]*0.5)

"Percentage of units with low-flow toilets"[Urban and Regional]= INTEG (increasing units rate （LF toilet）[Urban and Regional]-"decreasing units (LF toilet)"\[Urban and Regional],initial percentage of units with low flow appliances[ici,Urban and Regional]), {UNIT: Dmnl}

Regional Population Share of Total Population=Lookup of Regional Share(Time)

population increasing=IF THEN ELSE(Time<=1252,Historical Weekly Increasing Population[Urban], Urban Population*Future increasing rate/52/100)

Population[Urban]=Urban Population

Population[Regional]=Regional Population

Lookup of Regional Share=GET XLS LOOKUPS('?ALI Municipal', 'Population' ,'M' , 'N3')

Regional Population=Total Population*Regional Population Share of Total Population

Future increasing rate=IF THEN ELSE(Time>1200, IF THEN ELSE(Population Scenario Selection = 1 , "Increasing rate (Low)"\(Time)*100 , IF THEN ELSE(Population Scenario Selection = 2 , "Increasing rate (High)"\(Time)*100, Increasing rate assumption)),0)

Urban Population= INTEG (INTEGER(population increasing),619870)

Total Population=Urban Population/(1-Regional Population Share of Total Population)

percentage outdoor demand reduction from xeriscaping[Urban and Regional]=
current week percentage of homes with xeriscaping[Urban and Regional]*constant xeriscaping multiplier\[Urban and Regional]

actual daily demand in=Historical observed weekly water demand/7

Percentage of units with BATs[Urban and Regional]= INTEG ("increasing units rate (BAT)"[Urban and Regional],0), {UNIT: Dmnl}

"lookup of effect （BAT units)"([(0,0)-(1,1)],(0,0),(0.5,1),(1,0.01))

"effect of gap (BAT units)"[Urban and Regional]="lookup of effect （BAT units)"("gap (units BAT)"[Urban and Regional\]/maximum percentage of units with BAT[Urban and Regional])

per capita daily municipal water demand by category[toilet,Urban and Regional]=base per capita daily municipal water demand by category[toilet,Urban and Regional]*((1-Percentage of Houses Metered[toilet,Urban and Regional])*1+Percentage of Houses Metered\[toilet,Urban and Regional]*(1-water use reduction from water metering[toilet,Urban and Regional]))*((1-Percentage of Houses with BATs[Urban and Regional]-"Percentage of Houses with low-flow toilets"\[Urban and Regional])*1+"Percentage of Houses with low-flow toilets"[Urban and Regional\]*(1-water use reduction from low flow appliances[toilet,Urban and Regional])+Percentage of Houses with BATs\[Urban and Regional]*(1-Water reduction from BAT[toilet]))*(1-percentage water use reductions from grey water treatment and reuse[toilet,Urban and Regional\])*(1-water use reduction from education[toilet,Urban and Regional])

per capita daily municipal water demand by category[bath,Urban and Regional]=base per capita daily municipal water demand by category[bath,Urban and Regional]*((1-Percentage of Houses Metered[bath,Urban and Regional])*1+Percentage of Houses Metered\[bath,Urban and Regional]*(1-water use reduction from water metering[bath,Urban and Regional]))*((1-"Percentage of Houses with Low-Flow Appliances"[bath,Urban and Regional])*1+"Percentage of Houses with Low-Flow Appliances"[bath,Urban and Regional]*(1-water use reduction from low flow appliances[bath,Urban and Regional]))*(1-percentage water use reductions from grey water treatment and reuse[bath,Urban and Regional\])*(1-water use reduction from education[bath,Urban and Regional])

per capita daily municipal water demand by category[laundry,Urban and Regional]=base per capita daily municipal water demand by category[laundry,Urban and Regional]*((1-Percentage of

Houses Metered[laundry,Urban and Regional])*1+Percentage of Houses Metered\[laundry,Urban and Regional]*(1-water use reduction from water metering[laundry,Urban and Regional]))*((1-"Percentage of Houses with Low-Flow Appliances"[laundry,Urban and Regional])*1+\"Percentage of Houses with Low-Flow Appliances"[laundry,Urban and Regional]*(1-water use reduction from low flow appliances[laundry,Urban and Regional]))*(1-percentage water use reductions from grey water treatment and reuse[laundry,Urban and Regional\])*(1-water use reduction from education[laundry,Urban and Regional])

per capita daily municipal water demand by category[kitchen,Urban and Regional]=
base per capita daily municipal water demand by category[kitchen,Urban and Regional]*((1-Percentage of Houses Metered[kitchen,Urban and Regional])*1+Percentage of Houses Metered[kitchen,Urban and Regional]*(1-water use reduction from water metering[kitchen,Urban and Regional]))*((1-"Percentage of Houses with Low-Flow Appliances"[kitchen,Urban and Regional])*1+\"Percentage of Houses with Low-Flow Appliances"[kitchen,Urban and Regional]*(1-water use reduction from low flow appliances[kitchen,Urban and Regional]))*(1-percentage water use reductions from grey water treatment and reuse[kitchen,Urban and Regional\])*(1-water use reduction from education[kitchen,Urban and Regional])

per capita daily municipal water demand by category[leaks,Urban and Regional]=base per capita daily municipal water demand by category[leaks,Urban and Regional]
*((1-Percentage of Houses Metered[leaks,Urban and Regional])*1+Percentage of Houses Metered\[leaks,Urban and Regional]*(1-water use reduction from water metering[leaks,Urban and Regional]))*(1-percentage water use reduction from leaks management[leaks,Urban and Regional])*(1-water use reduction from education[leaks,Urban and Regional])

per capita daily municipal water demand by category[other,Urban and Regional]=base per capita daily municipal water demand by category[other,Urban and Regional]*(\(1-Percentage of Houses Metered[other,Urban and Regional])*1+Percentage of Houses Metered[other,Urban and Regional]*(1-water use reduction from water metering[other,Urban and Regional]))*(1-water use reduction from education[other,Urban and Regional])

per capita daily municipal water demand by category[outdoor,Urban and Regional]=(base per capita daily municipal water demand by category[outdoor,Urban and Regional\]-IF THEN ELSE(base per capita daily municipal water demand by category[outdoor,Urban and Regional]<(water use reudction from rain barrels[outdoor,Urban and Regional\]*Percentage of Houses with Rain Barrels[Urban and Regional]+water use reduction from education[outdoor,Urban and Regional])\, 0 , water use reudction from rain barrels[outdoor,Urban and Regional]*Percentage of Houses with Rain Barrels[Urban and Regional\]+water use reduction from education[outdoor,Urban and Regional]))
*((1-Percentage of Houses Metered[outdoor,Urban and Regional])*1+Percentage of Houses Metered\[outdoor,Urban and Regional]*(1-water use reduction from water metering[outdoor,Urban and Regional]))*(1-water use reduction from education[outdoor,Urban and Regional])

per capita daily municipal water demand by category[nonrevenue,Urban and Regional]=base per capita daily municipal water demand by category[nonrevenue,Urban and Regional\]*((1-

Percentage of Houses Metered[nonrevenue,Urban and Regional])*1+Percentage of Houses Metered\[nonrevenue,Urban and Regional]*(1-water use reduction from water metering[nonrevenue,Urban and Regional]))*(1-water use reduction from education[nonrevenue,Urban and Regional]) per capita daily municipal water demand by category[ici,Urban and Regional]=daily water demand by category[ici,Urban and Regional]/Population[Urban and Regional\]*1e+09 per capita daily municipal water demand by category[multires,Urban and Regional]=daily water demand by category[multires,Urban and Regional]/Population[Urban and Regional\]*1e+09, {UNIT: lpcd}

"gap (units BAT)"[Urban and Regional]=maximum percentage of units with BAT[Urban and Regional]-Percentage of units with BATs\[Urban and Regional]

"base adoption rate(BAT unit)"[Urban]=0.003 "base adoption rate(BAT unit)"[Regional]=0

maximum percentage of units with BAT[Urban and Regional]=0.9, {UNIT: Dmnl}

"increasing units rate (BAT)"[Urban and Regional]=IF THEN ELSE(Percentage of units with BATs[Urban and Regional]+"base adoption rate(BAT unit)"\[Urban and Regional]*"effect of gap (BAT units)"[Urban and Regional]>0.9,\ 0.9-Percentage of units with BATs[Urban and Regional] , IF THEN ELSE(Time<"application time (BAT)"[Urban and Regional], 0,"base adoption rate(BAT unit)"[Urban and Regional]*"effect of gap (BAT units)"\[Urban and Regional]))

"Percentage of units with old high-flow toilet"[Urban]= INTEG (-"decreasing units (HF toilet)"[Urban],0.95) "Percentage of units with old high-flow toilet"[Regional]= INTEG (-"decreasing units (HF toilet)"[Regional],0.94), {UNIT: fraction}

"decreasing units (LF toilet)"[Urban and Regional]=IF THEN ELSE("Percentage of units with low-flow toilets"[Urban and Regional]=0, 0 , IF THEN ELSE("Percentage of units with low-flow toilets"[Urban and Regional]-"increasing units rate (BAT)"\[Urban and Regional]<0,"Percentage of units with low-flow toilets"[Urban and Regional\], IF THEN ELSE("decreasing units (HF toilet)"[Urban and Regional]=0, "increasing units rate (BAT)"\[Urban and Regional], "increasing units rate (BAT)"[Urban and Regional]*0.88\)))

annual unmet demand=IF THEN ELSE("annual unmet demand (bar)"=0, :NA: , "annual unmet demand (bar)"), {UNIT: ML}

"annual unmet demand (bar)"=avarage daily unmet demand*365, {UNIT: ML}

percentage of annual unmet demand=IF THEN ELSE(annual unmet demand=:NA:, :NA:, annual unmet demand/"total annual demand (line)"\), {UNIT: fraction}

percentage of annual unmet water demand=IF THEN ELSE(Time<52, :NA: , Annual Municipal Unmet Demand/Annual Municipal Demand)

avarage daily unmet demand=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative unmet water demand/52,0), {UNIT: ML} cumulative annual unmet water demand= INTEG (unmet demand in-unmet demand out,0), {UNIT: ML}

daily unmet demand out=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative unmet water demand/TIME STEP\,0), {UNIT: ML}

daily unmet demand in=unmet water demand/7, {UNIT: ML}

unmet demand out=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative annual unmet water demand/TIME STEP\, 0), {UNIT: ML}IF THEN ELSE(MODULO(Time, 52.1775) > 51.2, cumulative weekly water \demand/TIME STEP, 0)

cumulative unmet water demand= INTEG (daily unmet demand in-daily unmet demand out,0), {UNIT: ML}

Annual Municipal Unmet Demand=SAMPLE IF TRUE(unmet demand out>0, unmet demand out, 0), {UNIT: ML}

unmet demand in=unmet water demand, {UNIT: MCM}

"Percentage of Houses with low-flow toilets"[Urban and Regional]= INTEG (increasing rate （LF toilet）[Urban and Regional]-"decreasing (LF toilet)"[Urban and Regional\],initial percentage of homes with low flow appliances[toilet,Urban and Regional]), {UNIT: Dmnl}

"application time (BAT)"[Urban]= GAME (50000)

"application time (BAT)"[Regional]=50000

"decreasing (HF toilet)"[Urban and Regional]=IF THEN ELSE("Percentage of houses with old high-flow toilet"[Urban and Regional]-increasing rate （LF toilet）\[Urban and Regional]-"increasing rate (BAT)"[Urban and Regional]*0.1<0, "Percentage of houses with old high-flow toilet"\[Urban and Regional],IF THEN ELSE("Percentage of houses with old high-flow toilet"[\Urban and Regional]=0, 0 , increasing rate （LF toilet）[Urban and Regional]+"increasing rate (BAT)"\[Urban and Regional]*0.12))

"gap (BAT)"[Urban and Regional]=
maximum percentage of houses with BAT[Urban and Regional]-Percentage of Houses with BATs\[Urban and Regional]

"base adoption rate(BAT)"[Urban]= GAME (0.003) "base adoption rate(BAT)"[Regional]=0.003

"increasing rate (BAT)"[Urban and Regional]=IF THEN ELSE(Percentage of Houses with BATs[Urban and Regional]+"base adoption rate(BAT)"\[Urban and Regional]*"effect of gap (BAT)"[Urban and Regional]>0.9, 0.9-Percentage of Houses with BATs\[Urban and Regional] , IF THEN ELSE(Time<"application time (BAT)"[Urban and Regional\], 0,"base adoption rate(BAT)"[Urban and Regional]*"effect of gap (BAT)"\[Urban and Regional]))

"lookup of effect （BAT)"([(0,0)-(1,1)],(0,0),(0.5,1),(1,0.01))

increasing rate （LF toilet）[Urban and Regional]=IF THEN ELSE(Time<"application time (BAT)"[Urban and Regional], low flow appliance change rate\[toilet,Urban and Regional],low flow appliance change rate[toilet,Urban and Regional\]*0.5)

"decreasing (LF toilet)"[Urban and Regional]=IF THEN ELSE("Percentage of Houses with low-flow toilets"[Urban and Regional]<0, 0 ,\ IF THEN ELSE("Percentage of Houses with low-flow toilets"[Urban and Regional]-"increasing rate (BAT)"\[Urban and Regional]<0,"Percentage of Houses with low-flow toilets"[Urban and Regional\], IF THEN ELSE("decreasing (HF toilet)"[Urban and Regional]=0, "increasing rate (BAT)"\[Urban and Regional], "increasing rate (BAT)"[Urban and Regional]*0.88)))

maximum percentage of houses with BAT[Urban and Regional]=0.9, {UNIT: Dmnl}

"effect of gap (BAT)"[Urban and Regional]="lookup of effect （BAT)"("gap (BAT)"[Urban and Regional]/maximum percentage of houses with BAT\[Urban and Regional])

Percentage of Houses with BATs[Urban and Regional]= INTEG ("increasing rate (BAT)"[Urban and Regional],0), {UNIT: Dmnl}

Water reduction from BAT[toilet]=0.98

Water reduction from BAT[ici]=0

Water reduction from BAT[multires]=0.6

"Percentage of houses with old high-flow toilet"[Urban]= INTEG (-"decreasing (HF toilet)"[Urban],0.95)

"Percentage of houses with old high-flow toilet"[Regional]= INTEG (-"decreasing (HF toilet)"[Regional],0.94), {UNIT: fraction}

"application # of low-flow toilet due to incentive"[Urban and Regional]=
IF THEN ELSE("Percentage of Houses with Low-Flow Appliances"[toilet,Urban and Regional\]<=0.45,increase rate of low flow appliance adoption with incentive[Urban and Regional\]*Population[Urban and Regional]/4, (maximum percentage of houses with low flow appliances\[toilet,Urban and Regional]-"Percentage of Houses with Low-Flow Appliances"[toilet,\Urban and Regional])*2.5*increase rate of low flow appliance adoption with incentive\[Urban and Regional]*Population[Urban and Regional]/4)

historical increase rate of rain barrels adoption with incentive[Urban and Regional]=IF THEN ELSE(historical incentive application time[Urban and Regional]=0 , 0 , base rain barrels increasing rate from incentive\[Urban and Regional])

adoption rate of low flow technologies[toilet,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[toilet,Urban and Regional]+increase rate of low flow appliance adoption with incentive\[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100), (base adoption rate of low flow technologies[toilet,Urban and Regional]+ increase rate of low flow appliance adoption with incentive\[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100))*low flow appliance application[Urban and Regional]))

adoption rate of low flow technologies[bath,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[bath,Urban and Regional]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances(unmet water demand/\100), (base adoption rate of low flow technologies[bath,Urban and Regional]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances(unmet water demand/\100))*low flow appliance application[Urban and Regional]))

adoption rate of low flow technologies[laundry,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[laundry,Urban and Regional]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances(unmet water demand/\100) , (base adoption rate of low flow technologies[laundry,Urban and Regional]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances(unmet water demand/\100))*low flow appliance application[Urban and Regional]))

adoption rate of low flow technologies[kitchen,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[kitchen,Urban and Regional]+increase rate of low flow appliance adoption with incentive\[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100) , (base adoption rate of low flow technologies[kitchen,Urban and Regional]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances(unmet water demand/\100))*low flow appliance application[Urban and Regional]))
adoption rate of low flow technologies[ici,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[ici,Urban and Regional\]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100) , (base adoption rate of low flow technologies[ici,Urban and Regional\]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand

on adoption rate of efficient appliances\(unmet water demand/100))*low flow appliance application[Urban and Regional]))

adoption rate of low flow technologies[multires,Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of low flow technologies[multires,Urban\]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100) , (base adoption rate of low flow technologies[multires,Urban\]+increase rate of low flow appliance adoption with incentive[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100))*low flow appliance application[Urban and Regional])), {UNIT: Dmnl}

increase rate of low flow appliance adoption with incentive[Urban and Regional]=IF THEN ELSE(Time<Future,IF THEN ELSE(if incentive applied in the past[Urban and Regional\]=0, 0 , IF THEN ELSE(Time>delay of historical incentive application time[Urban and Regional\],historical increase rate of low flow appliance adoption with incentive[Urban and Regional\],0)),delay of low flow increase rate with incentive[Urban and Regional]), {UNIT: Dmnl}

rain barrel increase rate with incentive[Urban and Regional]= GAME (historical increase rate of rain barrels adoption with incentive[Urban and Regional]\), {UNIT: fraction}

delay of low flow increase rate with incentive[Urban and Regional]= DELAY FIXED (low flow increase rate with incentive[Urban and Regional], IF THEN ELSE(low flow increase rate with incentive\[Urban and Regional]<=base low flow appliance adoption increasing rate with incentive\[Urban and Regional], 0 , 52), 0)

low flow increase rate with incentive[Urban and Regional]= GAME (historical increase rate of low flow appliance adoption with incentive[Urban and Regional\]), {UNIT: fraction}

historical increase rate of low flow appliance adoption with incentive[Urban and Regional\]=IF THEN ELSE(historical incentive application time[Urban and Regional]=0 , 0 , base low flow appliance adoption increasing rate with incentive\[Urban and Regional])

increase rate of rain barrel adoption with incentive[Urban and Regional]=IF THEN ELSE(Time<Future,IF THEN ELSE(if incentive applied in the past[Urban and Regional\]=0, 0 , IF THEN ELSE(Time>delay of historical incentive application time[Urban and Regional\],historical increase rate of rain barrels adoption with incentive[Urban and Regional\],0)),delay of rain barrel increase rate with incentive[Urban and Regional]), {UNIT: fraction}

if incentive applied in the past[Urban and Regional]=IF THEN ELSE(delay of historical incentive application time[Urban and Regional]=52, \0 , 1)

"actual total annual demand (line)"=IF THEN ELSE("actual total annual demand (bar)"=0, :NA: , "actual total annual demand (bar)"\ ), {UNIT: ML} actual annual observations[res]:=GET XLS DATA('?ALI Municipal', 'Validation' ,'B' , 'C3') actual annual observations[multi]:=GET XLS DATA('?ALI Municipal', 'Validation' ,'B' , 'F3') actual annual observations[region]:=GET XLS DATA('?ALI Municipal', 'Validation' ,'B' , 'D3') actual annual observations[comm]:=GET XLS DATA('?ALI Municipal', 'Validation' ,'B' , 'G3') actual annual observations[nonrev]:=GET XLS DATA('?ALI Municipal', 'Validation' ,'B' , 'E3'), {UNIT: ML}

annual demand by category（line）["(Rough) End-uses"]=IF THEN ELSE(annual demand by category（bar）["(Rough) End-uses"]=0, :NA: , annual demand by category（bar）\["(Rough) End-uses"]), {UNIT: ML}

"total annual demand (line)"=IF THEN ELSE("total annual demand (bar)"=0, :NA: , "total annual demand (bar)"), {UNIT: ML}

weekly water saving from education by category["End-uses"]=SUM(water use reduction from education["End-uses",Urban and Regional!]*Population[Urban and Regional\!]*7), {UNIT: liter}

total weekly water saving from education=SUM(weekly water saving from education by category["End-uses"!])/1e+09, {UNIT: MCM}

increase rate of treatment plant efficiency with upgrades=IF THEN ELSE(Time<delay of historical upgrades application time,0,IF THEN ELSE(Time>delay of future upgrades application time,historical increase rate of treatment plant capacity with upgrades\+delay of water plant efficiency increase rate with plant upgrades+historical increase rate of treatment plant capacity with upgrades*delay of water plant efficiency increase rate with plant upgrades,historical increase rate of treatment plant capacity with upgrades\)), {UNIT: fraction}

delay of historical expansion application time= future expansion application time+52

delay of historical upgrades application time=historical upgrade application time+52

future expansion application time= GAME (50000)

future upgrade application time= GAME (50000)

delay of future upgrades application time=IF THEN ELSE(future upgrade application time=1254, 500000, future upgrade application time\+52)

base weekly per capita outdoor water demand=IF THEN ELSE(INTEGER(MODULO(Time,52.1429))>16:AND:INTEGER(MODULO(Time, 52.1429))<38,IF THEN ELSE((0.00513971-0.221054*Hidden Neuron 1-0.458834*Hidden Neuron 2-0.679855*Hidden Neuron 3+1.1224*Hidden Neuron 4-1.60351*Hidden Neuron 5+1.11916*Hidden Neuron 6)*(1971.64-113.996)+113.996>0 , (0.00513971-0.221054*Hidden Neuron 1-0.458834*Hidden Neuron 2-0.679855*Hidden Neuron 3+1.1224*Hidden Neuron 4-1.60351*Hidden Neuron 5+1.11916*Hidden Neuron 6)*(1971.64-113.996)+113.996,0),IF THEN ELSE(Original Minimum Temperature>0:AND:Original Last Week's Minimum

Temperature>0:AND:Last Week's Outdoor Water Demand>0,(0.00513971-0.221054*Hidden Neuron 1-0.45883*Hidden Neuron 2-0.679855*Hidden Neuron 3+1.1224*Hidden Neuron 4-1.60351*Hidden Neuron 5+1.11916*Hidden Neuron 6)*(1971.64-113.996)+113.996,0)), {UNIT: lpcw}

daily per capita outdoor demand=SUM(daily water demand by category[outdoor,Urban and Regional!])/Total Population*1e+09

daily per capita municipal water demand=SUM(daily water demand by category["End-uses"!,Urban and Regional!])/Total Population*1e+09{UNIT: lpcd}

daily per capita residential demand=SUM(daily water demand by category[toilet,Urban and Regional!]+daily water demand by category\[bath,Urban and Regional!]+daily water demand by category[laundry,Urban and Regional\!]+daily water demand by category[kitchen,Urban and Regional!]+daily water demand by category\[leaks,Urban and Regional!]+daily water demand by category[other,Urban and Regional\!])/Total Population*1e+09

"# of , {UNIT: weeks}"=52.1775

withdrawal out=IF THEN ELSE(MODULO(Time, 52.1775)>51.18, cumulative weekly water withdrawal from streamflow\/TIME STEP,0), {UNIT: ML}

daily demand in[res]=daily urban residential water demand
daily demand in[comm]=daily urban ICI water demand
daily demand in[region]=daily regional water demand
daily demand in[multi]="daily urban multi-residential water demand"
daily demand in[nonrev]=daily urban nonrevenue water demand, {UNIT: ML}

actual daily demand out=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative actual daily total water demand\/TIME STEP,0), {UNIT: ML}

cumulative actual daily total water demand= INTEG (actual daily demand in-actual daily demand out,0), {UNIT: ML}

actual annual average daily water demand=IF THEN ELSE(MODULO(Time, 52.1778) > 51.18, cumulative actual daily total water demand\/52,0), {UNIT: ML}

"total annual demand (bar)"=SUM(annual demand by category（bar）["(Rough) End-uses"!]), {UNIT: ML}

"actual total annual demand (bar)"=actual annual average daily water demand*365, {UNIT: ML}

cumulative daily total water demand["(Rough) End-uses"]= INTEG (daily demand in["(Rough) End-uses"]-daily demand out["(Rough) End-uses"],0), {UNIT: ML} daily urban residential water demand=daily residential indoor water demand[Urban]+daily residential outdoor water demand[\Urban], {UNIT: ML}

"(Rough) End-uses":res, multi,region,comm,nonrev

annual demand by category（bar）["(Rough) End-uses"]=annual average daily water demand["(Rough) End-uses"]*365, {UNIT: ML}

annual average daily water demand["(Rough) End-uses"]=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative daily total water demand["(Rough) End-uses"\]/52,0), {UNIT: ML}

daily demand out["(Rough) End-uses"]=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative daily total water demand["(Rough) End-uses"\]/TIME STEP,0), {UNIT: ML}

daily residential outdoor water demand[Urban and Regional]=daily water demand by category[outdoor,Urban and Regional], {UNIT: ML}

use in=weekly water use, {UNIT: MCM}

use out=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative weekly water use/TIME STEP, \0), {UNIT: MCM}IF THEN ELSE(MODULO(Time, 52.1775) > 51.2, cumulative weekly water \demand/TIME STEP, 0)

cumulative weekly water use= INTEG (use in-use out,0), {UNIT: MCM}

withdrawal in=IF THEN ELSE(refilling > 0 ,"weekly total water demand （in-city & regional）"+refilling\ ,IF THEN ELSE("weekly total water demand （in-city & regional）"< maximum supply from streamflow\,"weekly total water demand （in-city & regional）" , maximum supply from streamflow\ ))IF THEN ELSE(refilling > 0 ,"weekly total water demand （in-city & \regional）"+refilling , maximum supply from streamflow) , {UNIT: MCM}

maximum supply from allocation=weekly water allocation under licences*WTP efficiency, {UNIT: ML}

maximum supply from streamflow=MIN(maximum supply from allocation, WTP production capacity), {UNIT: ML}

refillable supply=IF THEN ELSE("weekly total water demand （in-city & regional）"<maximum supply from streamflow\, maximum supply from streamflow -"weekly total water demand （in-city & regional）", 0)

Annual Municipal Use=SAMPLE IF TRUE(use out>0, use out, 0), {UNIT: MCM}

Reservoir Storage= INTEG (refilling-withdrawal from reservoir,"E.L. Smith weekly storage"+Rossdale weekly storage), {UNIT: ML} withdrawal from reservoir=IF THEN ELSE(Reservoir Storage>0:AND:withdrawal demand>0, MIN(Reservoir Storage, withdrawal demand\), 0), {UNIT: ML}

daily urban ICI water demand=daily water demand by category[ici,Urban], {UNIT: ML}

"daily urban multi-residential water demand"=daily water demand by category[multires,Urban], {UNIT: ML}

daily urban nonrevenue water demand=daily water demand by category[nonrevenue,Urban], {UNIT: ML}

"increase , {UNIT: weeks} demand>supply"=IF THEN ELSE(unmet water demand >0, 1 , 0), {UNIT: weeks}

refilling=IF THEN ELSE(Reservoir Storage<"E.L. Smith weekly storage"+Rossdale weekly storage:AND:\refillable supply>0, MIN(Rossdale weekly storage+"E.L. Smith weekly storage"-Reservoir Storage, refillable supply\), 0), {UNIT: ML}

weekly water supply=maximum supply from streamflow+withdrawal from reservoir, {UNIT: ML}

withdrawal demand=IF THEN ELSE("weekly total water demand （in-city & regional）">maximum supply from streamflow\, "weekly total water demand （in-city & regional）"-maximum supply from streamflow , 0), {UNIT: ML}

weekly water use=MIN(weekly water supply,"weekly total water demand （in-city & regional）"), {UNIT: ML}weekly water withdrawal*WTP efficiency

weekly water withdrawal=0, {UNIT: MCM}

"increase , {UNIT: weeks} demand>capacity"=IF THEN ELSE("weekly total water demand （in-city & regional）">maximum supply from streamflow\, 1 , 0), {UNIT: weeks}

unmet water demand=IF THEN ELSE(withdrawal from reservoir>=withdrawal demand , 0 , withdrawal demand-withdrawal from reservoir\), {UNIT: ML}

daily residential indoor water demand[Urban and Regional]=daily water demand by category[toilet,Urban and Regional]+daily water demand by category[bath,Urban and Regional]+daily water demand by category[laundry,Urban and Regional]+daily water demand by category[kitchen,Urban and Regional]+daily water demand by category[leaks,Urban and Regional]+daily water demand by category[other,Urban and Regional], {UNIT: ML}

maximum percentage of units with low flow appliances[ici,Urban and Regional]=base max BAT rate[ici,Urban and Regional]*(1+education impact on water efficient appliances\)

maximum percentage of units with low flow appliances[multires,Urban and Regional]=base max BAT rate[multires,Urban and Regional]*(1+education impact on water efficient appliances\)

daily regional water demand=SUM(daily water demand by category["End-uses"!,Regional]), {UNIT: ML}

"gap (low-flow houses)"[indoor,Urban and Regional]=maximum percentage of houses with low flow appliances[indoor,Urban and Regional]-"Percentage of Houses with Low-Flow Appliances"\[indoor,Urban and Regional]

"lookup of effect (rain barrels)"([(0,0)-(10,10)],(0,0),(0.1,0.1),(1,1))

"lookup of effect （low-flow houses）"([(0,0)-(1,1)],(0,0),(0.5,1),(1,0))

"effect of gap (rain barrels)"[Urban and Regional]="lookup of effect (rain barrels)"("gap (rain barrels)"[Urban and Regional]/maximum percentage of houses with rain barrels\[Urban and Regional])

low flow appliance change rate[toilet,Urban and Regional]=adoption rate of low flow technologies[toilet,Urban and Regional]*"effect of gap (low-flow houses)"\[toilet,Urban and Regional]

low flow appliance change rate[bath,Urban and Regional]=adoption rate of low flow technologies[bath,Urban and Regional]*"effect of gap (low-flow houses)"\[bath,Urban and Regional]

low flow appliance change rate[laundry,Urban and Regional]=adoption rate of low flow technologies[laundry,Urban and Regional]*"effect of gap (low-flow houses)"\[laundry,Urban and Regional]

low flow appliance change rate[kitchen,Urban and Regional]=adoption rate of low flow technologies[kitchen,Urban and Regional]*"effect of gap (low-flow houses)"\[kitchen,Urban and Regional], {UNIT: Dmnl}
IF THEN ELSE(Percentage of Houses with Low Flow Appliances[municipal subsectors]<1, \IF THEN ELSE(Percentage of Houses with Low Flow Appliances[municipal \subsectors]+adoption rate of low flow technologies[municipal \subsectors]<1,adoption rate of low flow technologies[municipal subsectors], 1-Percentage of Houses with Low Flow \Appliances[municipal subsectors]),0)

rain barrel change rate[Urban and Regional]=adoption rate of rain barrels[Urban and Regional]*"effect of gap (rain barrels)"[Urban and Regional\], {UNIT: Dmnl}

"gap (rain barrels)"[Urban and Regional]=maximum percentage of houses with rain barrels[Urban and Regional]-Percentage of Houses with Rain Barrels\[Urban and Regional] "effect of gap (low-flow houses)"[toilet,Urban and Regional]="lookup of effect （low-flow houses）"("gap (low-flow houses)"[toilet,Urban and Regional\]/maximum percentage of houses with low flow appliances[toilet,Urban and Regional])\

"effect of gap (low-flow houses)"[bath,Urban and Regional]="lookup of effect （low-flow houses）"("gap (low-flow houses)"[bath,Urban and Regional\]/maximum percentage of houses with low flow appliances[bath,Urban and Regional])

"effect of gap (low-flow houses)"[laundry,Urban and Regional]="lookup of effect （low-flow houses）"("gap (low-flow houses)"[laundry,Urban and Regional\]/maximum percentage of houses with low flow appliances[laundry,Urban and Regional]\)

"effect of gap (low-flow houses)"[kitchen,Urban and Regional]="lookup of effect （low-flow houses）"("gap (low-flow houses)"[kitchen,Urban and Regional\]/maximum percentage of houses with low flow appliances[kitchen,Urban and Regional]\)

"low flow appliance change rate (units)"[ici,Urban and Regional]=adoption rate of low flow technologies[ici,Urban and Regional]*"effect of gap (low-flow units)"\[ici,Urban and Regional]

"low flow appliance change rate (units)"[multires,Urban and Regional]=adoption rate of low flow technologies[multires,Urban and Regional]*"effect of gap (low-flow units)"\[multires,Urban and Regional]"

lookup of effect （low-flow units）"([(0,0)-(10,10)],(0,0),(0.5,1),(1,0))

"effect of gap (low-flow units)"[ici,Urban and Regional]="lookup of effect （low-flow units）"("gap (low-flow units)"[ici,Urban and Regional\]/maximum percentage of units with low flow appliances[ici,Urban and Regional])

"effect of gap (low-flow units)"[multires,Urban and Regional]="lookup of effect （low-flow units）"("gap (low-flow units)"[multires,Urban and Regional\]/maximum percentage of units with low flow appliances[multires,Urban and Regional]\)

"gap (low-flow units)"[ici,Urban and Regional]=maximum percentage of units with low flow appliances[ici,Urban and Regional]-Percentage of Units with Low Flow Appliances\[ici,Urban and Regional]

"gap (low-flow units)"[multires,Urban and Regional]=maximum percentage of units with low flow appliances[multires,Urban and Regional]-Percentage of Units with Low Flow Appliances\[multires,Urban and Regional]

base per unit daily municipal water demand by category[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I3')
base per unit daily municipal water demand by category[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K3')

base per unit daily municipal water demand by category[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K27')
base per unit daily municipal water demand by category[ici,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I27'){UNIT: lpcd}

initial percentage of units with low flow appliances[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I7')
initial percentage of units with low flow appliances[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K7')
initial percentage of units with low flow appliances[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K31')
initial percentage of units with low flow appliances[ici, Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I31'), {UNIT: Dmnl}

Percentage of Units with Low Flow Appliances[ici,Urban and Regional]= INTEG ("low flow appliance change rate (units)"[ici,Urban and Regional],initial percentage of units with low flow appliances[ici,Urban and Regional]) Percentage of Units with Low Flow Appliances[multires,Urban and Regional]= INTEG ("low flow appliance change rate (units)"[multires,Urban and Regional],initial percentage of units with low flow appliances[multires,Urban and Regional])

indoor:toilet,bath,laundry,kitchen

"Increasing rate (Low)"(GET XLS LOOKUPS('?ALI Municipal', 'Population' ,'H' , 'I3'))

Population Scenario Selection= GAME (1)

"Increasing rate (High)"(GET XLS LOOKUPS('?ALI Municipal', 'Population' ,'H' , 'J3'))

base increase rate of treatment plant capacity by expansion=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B19')

daily water demand by category[toilet,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[toilet\,Urban and Regional]/1e+06

daily water demand by category[bath,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[bath\,Urban and Regional]/1e+06

daily water demand by category[laundry,Urban and Regional]=
Population[Urban and Regional]*per capita daily municipal water demand by category[laundry\,Urban and Regional]/1e+06

daily water demand by category[kitchen,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[kitchen\,Urban and Regional]/1e+06 daily water demand by category[leaks,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[leaks\,Urban and Regional]/1e+06

daily water demand by category[other,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[other\,Urban and Regional]/1e+06

daily water demand by category[outdoor,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[outdoor\,Urban and Regional]/1e+06

daily water demand by category[nonrevenue,Urban and Regional]=Population[Urban and Regional]*per capita daily municipal water demand by category[nonrevenue\,Urban and Regional]/1e+06

daily water demand by category[ici,Urban and Regional]="# of Commericals"[Urban and Regional]*per unit daily municipal water demand by category\[ici,Urban and Regional]/1e+06

daily water demand by category[multires,Urban and Regional]="# of Multi-residentials"[Urban and Regional]*per unit daily municipal water demand by category\[multires,Urban and Regional]/1e+06, {UNIT: ML}

increase rate of treatment plant capacity with expansion=IF THEN ELSE(future WTP capacity increase rate by expansion =base increase rate of treatment plant capacity by expansion\, IF THEN ELSE(Time<delay of historical expansion application time, 0 , IF THEN ELSE\(Time<Future, base increase rate of treatment plant capacity by expansion,delay of WTP capacity increase by expansion)), delay of WTP capacity increase by expansion), {UNIT: Dmnl}

future WTP capacity increase rate by expansion= GAME (base increase rate of treatment plant capacity by expansion), {UNIT: Dmnl}

water use reduction from education[toilet,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[toilet,Urban and Regional])

water use reduction from education[bath,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[bath ,Urban and Regional])

water use reduction from education[laundry,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[laundry,Urban and Regional])

water use reduction from education[kitchen,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , IF THEN ELSE(Time<Future, base education water saving[kitchen,Urban and Regional], education water saving of kitchen\
 ))

water use reduction from education[leaks,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[leaks,Urban and Regional])

water use reduction from education[other,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , IF THEN ELSE(Time<Future, base education water saving[other,Urban and Regional], education water saving of other\ ))

water use reduction from education[outdoor,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , IF THEN ELSE(Time<Future, base education water saving[outdoor,Urban and Regional], delay of education water saving of outdoor\[Urban and Regional]))

water use reduction from education[ici,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[ici,Urban and Regional])

water use reduction from education[nonrevenue,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[nonrevenue,Urban and Regional])

water use reduction from education[multires,Urban and Regional]=IF THEN ELSE(Time<delay of historical education application time[Urban and Regional]\, 0 , base education water saving[multires,Urban and Regional]){UNIT: lpcd}

Original Last Week's Precipitation=DELAY1(Original Precipitation, 1)

delay of humidifier standards water saving= DELAY FIXED (humidifier standards water saving, 52 , 0){UNIT: lpcd}

dishwasher rebates water saving= GAME (0), {UNIT: Dmnl}

softener standards water saving= GAME (0), {UNIT: Dmnl}

"# of Commericals"[Urban]=0.0149*Population[Urban]+ 5278.3 "# of Commericals"[Regional]=(0.0145*Population[Regional]+5878)/Population[Urban]*Population[Regional]"# of Multi-residentials"[Urban]=0.0023*Population[Urban] + 1622.6 "# of Multi-residentials"[Regional]=(0.0023*Population[Urban] + 1622.6)/Population[Urban]*Population[Regional]

Increasing rate assumption= GAME (1.3)

"Multi-residential Usage"[Urban and Regional]=1e-05*"# of Multi-residentials"[Urban and Regional] + 0.0102 delay of garburator prohibition water saving= DELAY FIXED (garburator prohibition water saving, 52 , 0){UNIT: lpcd}

Commercial Usage[Urban and Regional]=-3.6e-06*"# of Commericals"[Urban and Regional] + 0.1455

delay of softener standards water saving= DELAY FIXED (softener standards water saving, 52 , 0){UNIT: lpcd}

delay of dishwasher rebates water saving=DELAY FIXED(dishwasher rebates water saving, 52 , 0)

percentage of homes with water saving appliances of kitchen= GAME (1), {UNIT: Dmnl}

percentage of homes with water saving appliances of other= GAME (1), {UNIT: Dmnl}

garburator prohibition water saving= GAME (0), {UNIT: Dmnl}

humidifier standards water saving= GAME (0), {UNIT: Dmnl}

education water saving of kitchen=(delay of dishwasher rebates water saving+delay of garburator prohibition water saving\)*percentage of homes with water saving appliances of kitchen

education water saving of other=(delay of humidifier standards water saving+delay of softener standards water saving\)*percentage of homes with water saving appliances of other

"Percentage of Houses with Low-Flow Appliances"[toilet,Urban and Regional]= INTEG (low flow appliance change rate[toilet,Urban and Regional],initial percentage of homes with low flow appliances[toilet,Urban and Regional])

"Percentage of Houses with Low-Flow Appliances"[bath,Urban and Regional]= INTEG (low flow appliance change rate[bath,Urban and Regional],initial percentage of homes with low flow appliances[bath,Urban and Regional])

"Percentage of Houses with Low-Flow Appliances"[laundry,Urban and Regional]= INTEG (low flow appliance change rate[laundry,Urban and Regional],initial percentage of homes with low flow appliances[laundry,Urban and Regional])

"Percentage of Houses with Low-Flow Appliances"[kitchen,Urban and Regional]= INTEG (low flow appliance change rate[kitchen,Urban and Regional],initial percentage of homes with low flow appliances[kitchen,Urban and Regional]), {UNIT: Dmnl}

Percentage of Houses with Rain Barrels[Urban and Regional]= INTEG (rain barrel change rate[Urban and Regional],initial percentage of homes with rain barrels[Urban and Regional]) weekly water use by category["End-uses"]=ALLOCATE BY PRIORITY("weekly water demand by category （ in-city & regional ） "["End-uses"\], water use priority["End-uses"], ELMCOUNT("End-uses"), water use width, weekly water use), {UNIT: ML}

percentage water use reduction from leaks management[leaks,Urban and Regional]=IF THEN ELSE(Time<delay of histoical leaks management application time[Urban and Regional\], 0 , IF THEN ELSE(Time<Future, base decrease rate of leaks with leaks management[\leaks,Urban and Regional], delay of leaks decrease rate with leaks management[leaks\,Urban and Regional])), {UNIT: fraction}

Percentage of Houses Metered["End-uses",Urban and Regional]= INTEG (water metering change rate["End-uses",Urban and Regional],initial percentage of homes metered["End-uses",Urban and Regional]), {UNIT: Dmnl}

Last week's Population[Urban and Regional]= DELAY FIXED (Population[Urban and Regional],1,0), {UNIT: Dmnl}

demand in="weekly total water demand （in-city & regional）", {UNIT: MCM}

new homes with greywater treatment requirement[Urban and Regional]=IF THEN ELSE("current week # of homes with greywater requirement"[Urban and Regional\]>="last week # of homes with greywater requirement"[Urban and Regional],"current week # of homes with greywater requirement"[Urban and Regional]-"last week # of homes with greywater requirement"\[Urban and Regional] , 0), {UNIT: Dmnl}

current week percentage of homes with greywater treatment[Urban and Regional]=homes with greywater treatment[Urban and Regional]/(Population[Urban and Regional]/4\)
, {UNIT: fraction}

homes with greywater treatment application[Urban and Regional]= DELAY FIXED (new homes with greywater treatment requirement[Urban and Regional],delay of greywater application\,0), {UNIT: Dmnl}

homes with xeriscaping[Urban and Regional]= INTEG (xeriscaping conversion[Urban and Regional],0), {UNIT: Dmnl}

"daily water demand by category （in-city & regional）"["End-uses"]=SUM(daily water demand by category["End-uses",Urban and Regional!]), {UNIT: ML}

last week percentage of homes with greywater requirement[Urban and Regional]= DELAY FIXED\ (percentage of homes with greywater treatment[Urban and Regional]*greywater treatment\[Urban and Regional],1,0), {UNIT: Dmnl}

last week percentage of homes with xeriscaping requirement[Urban and Regional]= DELAY FIXED\ (percentage of homes with xeriscaping[Urban and Regional]*xeriscaping[Urban and Regional\],1,0) xeriscaping conversion[Urban and Regional]=weekly new homes xeriscaping conversion[Urban and Regional], {UNIT: Dmnl}

"current week # of homes with greywater requirement"[Urban and Regional]=Population[Urban and Regional]/4*percentage of homes with greywater treatment[Urban and Regional\]*greywater treatment[Urban and Regional]

new homes with xeriscaping requirement[Urban and Regional]=IF THEN ELSE("current week # of homes with xeriscaping requirement"[Urban and Regional\]>="last week # of homes with xeriscaping requirement"[Urban and Regional], "current week # of homes with xeriscaping requirement"[Urban and Regional]-"last week # of homes with xeriscaping requirement"\[Urban and Regional] , 0), {UNIT: Dmnl}

"Non- revenue"[Urban and Regional]=(daily water demand by category[nonrevenue,Urban and Regional])*1000

"non-reasonal weekly total water demand"[Urban and Regional]=SUM(weekly water demand by category[nonseasonal!,Urban and Regional])

weekly new homes xeriscaping conversion[Urban and Regional]=cumulative new homes with xeriscaping requirement[Urban and Regional]/delay of xeriscaping conversion, {UNIT: Dmnl}

homes with greywater treatment[Urban and Regional]= INTEG (greywater treatment application[Urban and Regional],0), {UNIT: Dmnl}

cumulative new homes with greywater treatment requirement[Urban and Regional]= INTEG \(new homes with greywater treatment requirement[Urban and Regional]-homes with greywater treatment application\[Urban and Regional],0), {UNIT: Dmnl}

cumulative new homes with xeriscaping requirement[Urban and Regional]= INTEG (new homes with xeriscaping requirement[Urban and Regional]-homes with xeriscaping conversion\[Urban and Regional],0), {UNIT: Dmnl}

"last week # of homes with xeriscaping requirement"[Urban and Regional]=Last week's Population[Urban and Regional]/4*last week percentage of homes with xeriscaping requirement\[Urban and Regional], {UNIT: Dmnl}

"current week # of homes with xeriscaping requirement"[Urban and Regional]=Population[Urban and Regional]/4*percentage of homes with xeriscaping[Urban and Regional\]*xeriscaping[Urban and Regional], {UNIT: Dmnl}

greywater treatment application[Urban and Regional]=weekly new homes with greywater application[Urban and Regional], {UNIT: Dmnl} current week percentage of homes with xeriscaping[Urban and Regional]=homes with xeriscaping[Urban and Regional]/(Population[Urban and Regional]/4), {UNIT: fraction}

weekly new homes with greywater application[Urban and Regional]=cumulative new homes with greywater treatment requirement[Urban and Regional]/delay of greywater application, {UNIT: Dmnl}

"weekly total water demand （in-city & regional）"=SUM(weekly total water demand[Urban and Regional!]), {UNIT: ML}

homes with xeriscaping conversion[Urban and Regional]= DELAY FIXED (new homes with xeriscaping requirement[Urban and Regional],delay of xeriscaping conversion\,0), {UNIT: Dmnl}

"weekly water demand by category （in-city & regional）"["End-uses"]=SUM(weekly water demand by category["End-uses",Urban and Regional!]), {UNIT: ML}

percentage water use reductions from grey water treatment and reuse[toilet,Urban and Regional\]=current week percentage of homes with greywater treatment[Urban and Regional]*constant grey water and reuse multipliers\[toilet,Urban and Regional]
percentage water use reductions from grey water treatment and reuse[bath,Urban and Regional\]=0
percentage water use reductions from grey water treatment and reuse[laundry,Urban and Regional\]=0
percentage water use reductions from grey water treatment and reuse[kitchen,Urban and Regional\]=0
percentage water use reductions from grey water treatment and reuse[ici,Urban and Regional\]=0
percentage water use reductions from grey water treatment and reuse[multires,Urban and Regional\]=current week percentage of homes with greywater treatment[Urban and Regional]*constant grey water and reuse multipliers\[multires,Urban and Regional], {UNIT: fraction}

weekly water demand by category["End-uses",Urban and Regional]=daily water demand by category["End-uses",Urban and Regional]*7, {UNIT: ML}

weekly total water demand[Urban and Regional]=SUM(weekly water demand by category["End-uses"!,Urban and Regional]), {UNIT: ML}

"last week # of homes with greywater requirement"[Urban and Regional]=Last week's Population[Urban and Regional]/4*last week percentage of homes with greywater requirement\[Urban and Regional], {UNIT: Dmnl}

adoption rate of rain barrels[Urban and Regional]= GAME (IF THEN ELSE(Time<Future, base adoption rate of rain barrels[Urban and Regional]+increase rate of rain barrel adoption with incentive\[Urban and Regional]+effect of unmet demand on adoption rate of efficient appliances\(unmet water demand/100) , (base adoption rate of rain barrels[Urban and Regional]+increase rate of rain barrel adoption with incentive\[Urban and Regional]+effect of

unmet demand on adoption rate of efficient appliances\(unmet water demand/100))*rain barrels application[Urban and Regional])), {UNIT: Dmnl}

leaks decrease rate with leaks management[Urban and Regional]= GAME (base decrease rate of leaks with leaks management[leaks,Urban]), {UNIT: fraction}

delay of historical incentive application time[Urban and Regional]=historical incentive application time[Urban and Regional]+52, {UNIT: Dmnl}

maximum percentage of houses with low flow appliances[toilet,Urban and Regional]=base max BAT rate[toilet,Urban and Regional]*(1+education impact on water efficient appliances\)

maximum percentage of houses with low flow appliances[bath,Urban and Regional]=base max BAT rate[bath,Urban and Regional]*(1+education impact on water efficient appliances\)

maximum percentage of houses with low flow appliances[laundry,Urban and Regional]=base max BAT rate[laundry,Urban and Regional]*(1+education impact on water efficient appliances\)

maximum percentage of houses with low flow appliances[kitchen,Urban and Regional]=base max BAT rate[kitchen,Urban and Regional]*(1+education impact on water efficient appliances\), {UNIT: Dmnl}

maximum percentage of houses with rain barrels[Urban and Regional]=base max rain barrel rate[Urban and Regional]*(1+education impact on water efficient appliances\), {UNIT: Dmnl}

education water saving of outdoor[Urban and Regional]= GAME (base education water saving[outdoor,Urban and Regional]), {UNIT: Dmnl}

increase of metering rate["End-uses",Urban and Regional]=base increase rate of metering["End-uses",Urban and Regional], {UNIT: Dmnl}

delay of education water saving of outdoor[Urban and Regional]= DELAY FIXED (education water saving of outdoor[Urban and Regional],IF THEN ELSE(education water saving of outdoor\[Urban and Regional]<=base education water saving[outdoor,Urban and Regional], 0 , \52),0){UNIT: lpcd}

delay of histoical leaks management application time[Urban and Regional]=histoical leaks management application time[Urban and Regional], {UNIT: Dmnl}histoical leaks management application time+52

delay of historical education application time[Urban and Regional]=historical education application time[Urban and Regional]+52, {UNIT: Dmnl}

delay of leaks decrease rate with leaks management[leaks,Urban and Regional]= DELAY FIXED\ (leaks decrease rate with leaks management[Urban and Regional], IF THEN ELSE(leaks decrease rate with leaks management\[Urban and Regional]<=base decrease rate of leaks with leaks management[leaks,Urban and Regional\], 0 , 52), 0)

water metering change rate["End-uses",Urban and Regional]=IF THEN ELSE(Percentage of Houses Metered["End-uses",Urban and Regional]<1, IF THEN ELSE\(Percentage of Houses Metered["End-uses",Urban and Regional]+increase of metering rate\["End-uses",Urban and Regional]<1,increase of metering rate["End-uses",Urban and Regional\], 1-Percentage of Houses Metered["End-uses",Urban and Regional]),0)

delay of rain barrel increase rate with incentive[Urban and Regional]= DELAY FIXED (rain barrel increase rate with incentive[Urban and Regional],IF THEN ELSE(rain barrel increase rate with incentive\[Urban and Regional]<=base rain barrels increasing rate from incentive[Urban and Regional\], 0, 52), 0)

Urban and Regional:Urban,Regional

Historical Weekly Increasing Population[Urban]=LOOKUP SLOPE(Historical Population Lookup[Urban], Time, 1)
Historical Weekly Increasing Population[Regional]=LOOKUP SLOPE(Historical Population Lookup[Regional], Time, 1)

nonseasonal:toilet, bath, laundry, kitchen, leaks, other, ici, nonrevenue

Future=1254

Original Precipitation=IF THEN ELSE(RCP Scenario= 1, "Precip 2.6" , IF THEN ELSE(RCP Scenario=2, "Precip 4.5"\ , "Precip 8.5"))mm

"Maximum T 2.6":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'K2')

"Maximum T 4.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'G2')

"Maximum T 8.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'C2')

"Mean T 2.6":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'M2')

"Mean T 4.5":INTERPOLATE::=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'I2')

"Mean T 8.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'E2')

"Minimum T 2.6":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'L2')

"Minimum T 4.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'H2')

"Minimum T 8.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'D2')

"Precip 8.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'F2')

RCP Scenario= GAME (1)

"Precip 2.6":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'N2')

"Precip 4.5":=GET XLS DATA('? ALI Municipal input' , 'RCP', 'A' , 'J2')

Original Maximum Temperature=IF THEN ELSE(RCP Scenario= 1, "Maximum T 2.6" , IF THEN ELSE(RCP Scenario=2, "Maximum T 4.5"\ , "Maximum T 8.5"))°C

Original Mean Temperature=IF THEN ELSE(RCP Scenario= 1, "Mean T 2.6" , IF THEN ELSE(RCP Scenario=2, "Mean T 4.5"\ , "Mean T 8.5"))°C

Original Minimum Temperature=IF THEN ELSE(RCP Scenario= 1, "Minimum T 2.6" , IF THEN ELSE(RCP Scenario=2, "Minimum T 4.5"\ , "Minimum T 8.5"))mm

base per capita daily municipal water demand by category[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B3')

base per capita daily municipal water demand by category[bath,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C3')

base per capita daily municipal water demand by category[laundry,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D3')

base per capita daily municipal water demand by category[kitchen,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E3')

base per capita daily municipal water demand by category[leaks,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'F3')

base per capita daily municipal water demand by category[other,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'G3')

base per capita daily municipal water demand by category[outdoor,Urban]=IF THEN ELSE(Time<1055, base weekly per capita outdoor water demand/7 , base weekly per capita outdoor water demand\/7*(1-percentage outdoor demand reduction from xeriscaping[Urban]))

base per capita daily municipal water demand by category[nonrevenue,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'J3')

base per capita daily municipal water demand by category[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B27') base per capita daily municipal water demand by category[bath,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C27')

base per capita daily municipal water demand by category[laundry,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D27')

base per capita daily municipal water demand by category[kitchen,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E27')

base per capita daily municipal water demand by category[leaks,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'F27')

base per capita daily municipal water demand by category[other,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'G27')

base per capita daily municipal water demand by category[outdoor,Regional]=IF THEN ELSE(Time<1055,base weekly per capita outdoor water demand/7*Population[Regional\]/Population[Urban], base weekly per capita outdoor water demand/7*(1-percentage outdoor demand reduction from xeriscaping\[Urban])*Population[Regional]/Population[Urban])

base per capita daily municipal water demand by category[nonrevenue,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'J27'){UNIT: lpcd}

"Unexpected Change (Rainfall)"= GAME (0)

Scaled Last Week's Maximum Temperature=(Original Last Week's Maximum Temperature*(1+"Unexpected Change (Temperature)")-13.2)\/(35.1-13.2)

Scaled Last Week's Minimum Temperature=(Original Last Week's Minimum Temperature*(1+"Unexpected Change (Temperature)")-0)/(\15-0)

Scaled Last Week's Precipitation=(Original Last Week's Precipitation*(1+"Unexpected Change (Rainfall)")-0)/(99.2-0)

Scaled Last Week's Water Demand=(Last Week's Outdoor Water Demand-113.996)/(1971.64 - 113.996)

Scaled Maximum Temperature=(Original Maximum Temperature*(1+"Unexpected Change (Temperature)")-13.2)/(35.1-13.2\)

Scaled Mean Temperature=(Original Mean Temperature*(1+"Unexpected Change (Temperature)")-6.343)/(23.857-6.343\)

Scaled Minimum Temperature=(Original Minimum Temperature*(1+"Unexpected Change (Temperature)")-0)/(15-0)

Scaled Precipitation=(Original Precipitation*(1+"Unexpected Change (Rainfall)")-0)/(99.2-0)

Historical observed weekly water demand:INTERPOLATE::=GET XLS DATA('? ALI Municipal input' , 'Demand', 'A' , 'E2'), {UNIT: ML}

"Unexpected Change (Temperature)"= GAME (0)

Scaled Last Week's Mean Temperature=(Original Last Week's Mean Temperature*(1+"Unexpected Change (Temperature)")-6.343)/\(23.857-6.343)

Historical Population Lookup[Urban](GET XLS LOOKUPS('?ALI Municipal', 'Population' ,'B' , 'C3'))

Historical Population Lookup[Regional](GET XLS LOOKUPS('?ALI Municipal', 'Population' ,'B' , 'D3'))

Delayed Demand=DELAY FIXED(base weekly per capita outdoor water demand, 1 , 0)

Original Last Week's MaximumTemperature=DELAY1(Original Maximum Temperature,1)

Original Last Week's Mean Temperature=DELAY1(Original Mean Temperature, 1)

Original Last Week's Minimum Temperature=DELAY1(Original Minimum Temperature,1)

Original Last Week's Outdoor Water Demand=DELAY FIXED(Historical observed weekly per capita outdoor water Demand, 1 , 0), {UNIT: lpcw}

Hidden Neuron 1=1/(1+exp(-(8.11672-5.9389*Scaled Last Week's Water Demand-1.06279*Scaled Maximum Temperature+8.50525*Scaled Last Week's MaximumTemperature-1.78533*Scaled Minimum Temperature-1.63648*Scaled Last Week's Minimum Temperature-14.791*Scaled Mean Temperature+4.89521*Scaled Last Week's Mean Temperature-3.29304*Scaled Precipitation+7.55013*Scaled Last Week's Precipitation)))

Hidden Neuron 2=1/(1+exp(-(0.278458-3.5467*Scaled Last Week's Water Demand-0.755375*Scaled Maximum Temperature+1.42071*Scaled Last Week's Maximum Temperature-1.07646*Scaled Minimum Temperature-0.373518*Scaled Last Week's Minimum Temperature+0.617099*Scaled Mean Temperature+2.57032*Scaled Last Week's Mean Temperature+7.82811*Scaled Precipitation+0.74657*Scaled Last Week's Precipitation)))

Hidden Neuron 4=1/(1+exp(-(-0.180912-0.203895*Scaled Last Week's Water Demand+1.59962*Scaled Maximum Temperature+1.03965*Scaled Last Week's MaximumTemperature-0.889535*Scaled Minimum Temperature-1.43889*Scaled Last Week's Minimum Temperature-0.0698541*Scaled Mean Temperature+1.17326*Scaled Last Week's Mean Temperature+0.993593*Scaled Precipitation-0.275912*Scaled Last Week's Precipitation)))

Hidden Neuron 5=1/(1+exp(-(-0.795461-1.91001*Scaled Last Week's Water Demand+0.786043*Scaled Maximum Temperature-0.574868*Scaled Last Week's MaximumTemperature-0.96584*Scaled Minimum Temperature-0.46715*Scaled Last Week's Minimum Temperature+0.367519*Scaled Mean Temperature+0.95633*Scaled Last Week's Mean Temperature-0.393864*Scaled Precipitation -0.644673*Scaled Last Week's Precipitation)))

Hidden Neuron 6=1/(1+exp(-(1.04169-0.804249*Scaled Last Week's Water Demand+0.234891*Scaled Maximum Temperature-0.731802*Scaled Last Week's MaximumTemperature-0.2512*Scaled Minimum Temperature-0.169847*Scaled Last Week's Minimum Temperature+1.36084*Scaled Mean Temperature-1.20917*Scaled Last Week's Mean Temperature-1.12203*Scaled Precipitation -0.493468*Scaled Last Week's Precipitation)))

Last Week's Outdoor Water Demand=IF THEN ELSE(Time<1056, Original Last Week's Outdoor Water Demand , Delayed Demand), {UNIT: lpcw}

Hidden Neuron 3=1/(1+exp(-(0.175531-1.15225*Scaled Last Week's Water Demand+0.939437*Scaled Maximum Temperature+0.179819*Scaled Last Week's MaximumTemperature+0.577141*Scaled Minimum Temperature-1.40968*Scaled Last Week's Minimum Temperature-0.718333*Scaled Mean Temperature-1.06591*Scaled Last Week's Mean Temperature-0.0759527*Scaled Precipitation+0.103732*Scaled Last Week's Precipitation)))

Historical observed weekly per capita outdoor water Demand:INTERPOLATE::=GET XLS DATA('? ALI Municipal input' , 'Demand', 'A' , 'D2'), {UNIT: lpcw}

rain barrels application[Urban]= GAME (1)
rain barrels application[Regional]=1

low flow appliance application[Urban]= GAME (1)
low flow appliance application[Regional]=1, {UNIT: Dmnl}

effect of unmet demand on adoption rate of efficient appliances(GET XLS LOOKUPS('?BRSGM', 'Parameters' , '58' , 'B59')), {UNIT: Dmnl}

water use priority["End-uses"]=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B3'), {UNIT: Dmnl}

water use width=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B4'), {UNIT: Dmnl}

base WTP efficiency=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B5'), {UNIT: Dmnl}

WTP capacity utilization=weekly water use/WTP production capacity, {UNIT: Dmnl}

WTP efficiency=MIN(base WTP efficiency*(1+increase rate of treatment plant efficiency with upgrades\), 0.98), {UNIT: Dmnl}

base WTP production capacity=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B7'), {UNIT: MCM}

WTP production capacity=base WTP production capacity*(1+increase rate of treatment plant capacity with expansion\), {UNIT: MCM}

Annual Municipal Withdrawal=SAMPLE IF TRUE(withdrawal out>0,withdrawal out,0), {UNIT: ML}

Annual Municipal Demand=SAMPLE IF TRUE(demand out>0, demand out, 0), {UNIT: ML}

greywater treatment[Urban]= GAME (0)
greywater treatment[Regional]= GAME (0)

delay of greywater application=156, {UNIT: Dmnl}

delay of xeriscaping conversion=52, {UNIT: Dmnl}

xeriscaping[Urban]= GAME (0)
xeriscaping[Regional]= GAME (1)

constant xeriscaping multiplier[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H22')
constant xeriscaping multiplier[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H46'), {UNIT: Dmnl}

delay of education of water efficient appliances= DELAY FIXED (education of indoor water use, 52, 0)

base max rain barrel rate[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H14')
base max rain barrel rate[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H38'), {UNIT: Dmnl}

education of indoor water use= GAME (0), {UNIT: Dmnl}

education impact on water efficient appliances=delay of education of water efficient appliances*0.05, {UNIT: Dmnl}

weekly water allocation under licences= GAME (7500), {UNIT: ML}

base max BAT rate[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B10')
base max BAT rate[bath,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C10')

base max BAT rate[laundry,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D10')
base max BAT rate[kitchen,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E10')
base max BAT rate[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B34')
base max BAT rate[bath,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C34')
base max BAT rate[laundry,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D34')
base max BAT rate[kitchen,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E34')
base max BAT rate[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I10')
base max BAT rate[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K10')
base max BAT rate[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K34')
base max BAT rate[ici,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I34'), {UNIT: Dmnl}

delay of water plant efficiency increase rate with plant upgrades= DELAY FIXED (future water plant efficiency increase rate with plant upgrades,52,future water plant efficiency increase rate with plant upgrades\)

future water plant efficiency increase rate with plant upgrades= GAME (historical increase rate of treatment plant capacity with upgrades), {UNIT: fraction}

weekly water license=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B6'), {UNIT: MCM}

percentage of homes with greywater treatment[Urban]= GAME (0.8)
percentage of homes with greywater treatment[Regional]= GAME (0), {UNIT: Dmnl}

percentage of homes with xeriscaping[Urban]= GAME (0.8)
percentage of homes with xeriscaping[Regional]= GAME (0), {UNIT: Dmnl}

"E.L. Smith weekly storage"=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B9'), {UNIT: MCM}

Rossdale weekly storage=GET XLS CONSTANTS('?ALI Municipal', 'WTP & Allocation', 'B8'), {UNIT: MCM}

cumulative , {UNIT: weeks} of water demand exceeds total supply= INTEG ("increase , {UNIT: weeks} demand>supply",0)Week delay of WTP capacity increase by expansion= DELAY FIXED (future WTP capacity increase rate by expansion, 52 , 0)

cumulative , {UNIT: weeks} of demand exceeds WTP capacity= INTEG ("increase , {UNIT: weeks} demand>capacity",0)Week

cumulative weekly water withdrawal from streamflow= INTEG (withdrawal in-withdrawal out,0), {UNIT: ML}

demand out=IF THEN ELSE(MODULO(Time, 52.1775) > 51.18, cumulative weekly water demand/TIME STEP\, 0), {UNIT: ML}

cumulative weekly water demand= INTEG (demand in-demand out,0), {UNIT: ML}

historical education application time[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B50')
historical education application time[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C50'), {UNIT: Dmnl}

base decrease rate of leaks with leaks management[leaks,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'F15')
base decrease rate of leaks with leaks management[leaks,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'F39'), {UNIT: Dmnl}

base education water saving["End-uses",Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B16')
base education water saving["End-uses",Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B40'), {UNIT: Dmnl}

base low flow appliance adoption increasing rate with incentive[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B17') base low flow appliance adoption increasing rate with incentive[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B41'), {UNIT: Dmnl}

historical increase rate of treatment plant capacity with upgrades=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B20'), {UNIT: Dmnl}

base rain barrels increasing rate from incentive[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H18')

base rain barrels increasing rate from incentive[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H42'), {UNIT: Dmnl}

constant grey water and reuse multipliers[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B21')

constant grey water and reuse multipliers[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B45')
constant grey water and reuse multipliers[bath,Urban]=0
constant grey water and reuse multipliers[bath,Regional]=0
constant grey water and reuse multipliers[laundry,Urban]=0
constant grey water and reuse multipliers[laundry,Regional]=0
constant grey water and reuse multipliers[kitchen,Urban]=0
constant grey water and reuse multipliers[kitchen,Regional]=0
constant grey water and reuse multipliers[ici,Urban]=0
constant grey water and reuse multipliers[ici,Regional]=0
constant grey water and reuse multipliers[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K21')
constant grey water and reuse multipliers[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K45'), {UNIT: fraction}

historical incentive application time[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B52')
historical incentive application time[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C52'), {UNIT: Dmnl}

upgrades application time=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B53'), {UNIT: Dmnl}

histoical leaks management application time[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B51')
histoical leaks management application time[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C51'), {UNIT: Dmnl}

initial percentage of homes with low flow appliances[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B7')
initial percentage of homes with low flow appliances[bath,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C7')
initial percentage of homes with low flow appliances[laundry,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D7')
initial percentage of homes with low flow appliances[kitchen,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E7')
initial percentage of homes with low flow appliances[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I7')
initial percentage of homes with low flow appliances[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B31')
initial percentage of homes with low flow appliances[bath,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C31')
initial percentage of homes with low flow appliances[laundry,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D31')
initial percentage of homes with low flow appliances[kitchen,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E31')

initial percentage of homes with low flow appliances[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K7')
initial percentage of homes with low flow appliances[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K31'), {UNIT: Dmnl}

base adoption rate of low flow technologies[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B8')
base adoption rate of low flow technologies[bath,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C8')
base adoption rate of low flow technologies[laundry,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D8')
base adoption rate of low flow technologies[kitchen,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E8')
base adoption rate of low flow technologies[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I8')
base adoption rate of low flow technologies[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B32')
base adoption rate of low flow technologies[bath,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C32')
base adoption rate of low flow technologies[laundry,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D32')
base adoption rate of low flow technologies[kitchen,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E32')
base adoption rate of low flow technologies[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K8')
base adoption rate of low flow technologies[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K32')
base adoption rate of low flow technologies[ici,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I32'), {UNIT: Dmnl}

water use reduction from low flow appliances[toilet,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B9')
water use reduction from low flow appliances[bath,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C9')
water use reduction from low flow appliances[laundry,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D9')
water use reduction from low flow appliances[kitchen,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E9')
water use reduction from low flow appliances[ici,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I9')
water use reduction from low flow appliances[toilet,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B33')
water use reduction from low flow appliances[bath,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'C33')
water use reduction from low flow appliances[laundry,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'D33')

water use reduction from low flow appliances[kitchen,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'E33')
water use reduction from low flow appliances[multires,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K9')
water use reduction from low flow appliances[multires,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'K33')
water use reduction from low flow appliances[ici, Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'I33'), {UNIT: Dmnl}

water use reudction from rain barrels[outdoor,Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H13') water use reudction from rain barrels[outdoor,Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H37'){UNIT: lpcd}

base adoption rate of rain barrels[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H12')
base adoption rate of rain barrels[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H36'), {UNIT: Dmnl}

initial percentage of homes with rain barrels[Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H11')
initial percentage of homes with rain barrels[Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'H35'), {UNIT: Dmnl}

base increase rate of metering["End-uses",Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B5')
base increase rate of metering["End-uses",Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B29'), {UNIT: Dmnl}

initial percentage of homes metered["End-uses",Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B4')
initial percentage of homes metered["End-uses",Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B28'), {UNIT: Dmnl}

water use reduction from water metering["End-uses",Urban]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B6')
water use reduction from water metering["End-uses",Regional]=GET XLS CONSTANTS('?ALI Municipal', 'Parameters', 'B30'), {UNIT: fraction}

"End-uses":toilet, bath, laundry, kitchen, leaks, other, outdoor, ici, nonrevenue , multires

****
.Control
****
Simulation Control Parameters

FINAL TIME = 7000Week

The final time for the simulation.

INITIAL TIME = 0Week
The initial time for the simulation.

SAVEPER = TIME STEP Week [0,?]
The frequency with which output is stored.

TIME STEP = 1Week [0,?]
The time step for the simulation.