IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 7.39 ⋇ Vol. 11, Issue 4, April 2022

DOI: 10.17148/IJARCCE.2022.114114

Water Requirement Forecasting System

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Abstract: Water is essential for the survival of life on Earth. Both natural and manmade factors contribute to water scarcity. The amount of freshwater on Earth has stayed constant over time, but the human population has exploded. As a result, the search for freshwater becomes more intense every day. For improved and more effective water usage planning, proper management and forecasting are essential. The main parameters for an Urban Water Management are water demand and population forecasting. Machine learning is one of the most well-known forecasting approaches. Machine learning is a data analytics technology that allows machines to learn without having to be fully programmed. Machine learning, unlike previous demand forecasting approaches that were not ideal for historical unstructured and semi-structured data, takes into consideration or has the capability of assessing such data.

Keywords: water demand, forecasting, machine learning.

I. INTRODUCTION

Water is both a vital source of life and a valuable natural resource. Water covers nearly 70% of the earth's surface, and it is assumed that it will always be there for us; however, water shortages are already affecting multiple areas across continents. According to a recent UNESCO study, by 2025, 1.8 billion people living in multiple areas will face severe water shortages, and approximately 33% of the world's population will be under water stress conditions.

Desalination has become a major option for water delivery in recent decades, opening the door to tackling unconventional water resources with great promise for providing sustainable water supply. Desalination provides only around 1% of the world's drinking water, but it is increasing year after year.

Kuwait has a total area of 17,818 km2, a population of 4,62 million (2018), 98 percent of the Kuwait Metropolitan Area, 810 km2 or 4.5 percent of the total area, Kuwait is one of the few countries in the world without rivers or natural lakes, and Kuwait was entirely reliant on distillation plants for its freshwater supplies. Kuwait has been successfully using multi-stage flash distillation units for over 30 years. Kuwait has the greatest global water use per capita, with 500 gallons per person per day.

Desalinating seawater is more expensive than other natural resources such as groundwater or rivers because it requires a lot of energy; on the other hand, water recycling and conservation costs $1.09 to $2.49 per thousand gallons [4], with water demand forecasting lowering capture, treatment, storage, and distribution costs. The Water Distribution Network was able to reduce energy expenses by 5.2 percent while reducing energy consumption by 3.1 percent thanks to water demand projections.

The sustainability of economy & society development is to a large extent depending on rationalizing the utilization of water resources, for the last couple of decades desalination has become a vital alternative for water supply, It opens the door to tackle unconventional water resources that has great potentiality to provide sustainable water supply. Desalination offers just about 1% of the world's drinking water, but this amount is rising year-on-year.

State of Kuwait has a total area of 17,818 km2, Kuwait has a population of 4,62 million, roughly 98 percent of Kuwait Metropolitan Area, 810 km2 or 4.5 percent of the total area, Kuwait is one of few countries in the world without rivers or natural lakes, Kuwait was entirely dependent on distillation plants for its freshwater supplies. For about 30 years multi-stage flash distillation plants have been used successfully in Kuwait. The highest global water consumption per capita was recorded in Kuwait at 500 liters per person per day.

II. LITERATURE REVIEW

Shabani et al. [1] suggested a two-stage learning system that combines Gene Expression Programming (GEP) and time-series clustering to anticipate short-term water demand. The technique was put to the test in Milan, Italy, using real-world water demand data. Multi-scale modelling was done using lead intervals of 3, 6, 12, and 24 hours to rearrange hourly

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water demand patterns. The study found that when GEP is combined with unsupervised learning algorithms in comprehensive spherical k-means, more accurate findings are propagated.
Lopez et al. [2] proposed the Qualitative Multi-Model Predictor Plus (QMMP+), a multi-model predictor for water demand forecasting. A Nearest Neighbor (NN) classifier and a calendar were used to predict the quantitative element and analyse the pattern mode. Every period was run simultaneously with the NN classifier and the Calendar, and the best model for predicting was chosen using a probabilistic method. When applied to the Barcelona Water Distribution Network, the suggested model QMMP+ outperforms alternative methods such as Radial Basis Function Artificial Neural Networks, Autoregressive Integrated Moving Average, and Double Seasonal Holt-Winters. Water usage patterns unique modelling therapy boosts predicted precision, according to QMMP+.

Candelieri [3] proposed a fully data-driven and machine-learning-based strategy for characterising and forecasting short-term hourly water demand with an app based on two different data sources: urban water demand obtained from Supervisory Control and Data Acquisition (SCADA) and individual water usage obtained from automatic metre reading (AMR). On the data from the Milan water distribution network, an actual case study was conducted. The best and worst forecasting models were determined by grouping data at different time scales and then applying several SVM regression models over these clusters of data, with the obtained outcomes quantified by Mean Absolute Percentage Error (MAPE).

Lopez et al. [2] presented a multi-model predictor for water demand forecasting called Qualitative Multi-Model Predictor Plus (QMMP+). The quantitative element was predicted and the pattern mode was assessed using a Nearest Neighbor (NN) classifier and a calendar. Every period was executed concurrently with the NN classifier and the Calendar, and a probabilistic method was used to select the most suitable model for forecasting. In comparison with other methods such as Radial Basis Function Artificial Neural Networks, Autoregressive Integrated Moving Average and Double Seasonal Holt-Winters, the suggested model QMMP+ provides the highest outcomes when applied to the Barcelona Water Distribution Network. QMMP+ has shown that water usage patterns unique modeling therapy increases predictive precision.
Pacchin et al. [4] presented a model for forecasting water requirements in Castelfranco-Emilia city in Italy over a 24-hour time window using a two factors whose value is displayed at each forecast phase. The first factors reflect the percentage between the 24-hour average water supply following the moment the prediction is produced and the 24- hour average water demand. The second ratio reflects the connection between average water demand in a generic hour dropping over the 24-h forecast period and average water demand over that period, The results shows that the forecasting accuracy is generally high, with RMSE values ranging from 4 to 6 L/s and corresponding MAE percentages ranging from 5 to 7 percent.
Tiw et al. [5] made a Comparison of the daily urban water demand forecast using limited data extreme learning machine in combination with wavelet analysis (W) wavelet extreme learning machine (ELMW) or bootstrap (B) bootstrap-based extreme learning machine (ELMB) methods to the similar traditional artificial neural network-based models (i.e., ANN, ANNB, ANNW). ELMW model has been found to perform much better than ANN, ANNB, ANNW, and ELM models.
Al-Zahrani and AbMonasar [6] predict daily water demand in the future for the town of Al Khobar, Saudi Arabia by using time series models and Artificial Neural Networks (ANNs) depend on the daily water consumption and climate information. The result shows that using of the ANNs General Regression Neural Network (GRNN) model method with time series models is more efficient in water demand forecasting
Anele et al. [7] submitted an overview of short term water demand (STWD) forecasting techniques for water demand in South-Eastern Spain. This study shows that invariant time series (UTS) models such as (ARMA) and time series regression (TSR) models such as (ARMAX) can be combined with other techniques in a hybrid model such as ARMA and Feedforward back propagation neural network (FFBP-NN) may be counted as one of the accurate models for STWD forecasting.

III. METHODOLOGY

Problem statements:

1. To raise awareness of water availability in the city, as the demand for water supply has increased and some water is being wasted, certain substantial efforts have been required.
2. In this research, we will employ a machine learning meta-system to anticipate water availability in Pune using a robust probabilistic nonlinear regression approach.
3. To forecast future water availability and manage water as a sustainable resource.

Model framework:

The proposed framework that combines Face Net with liveness detection is shown in Figure1

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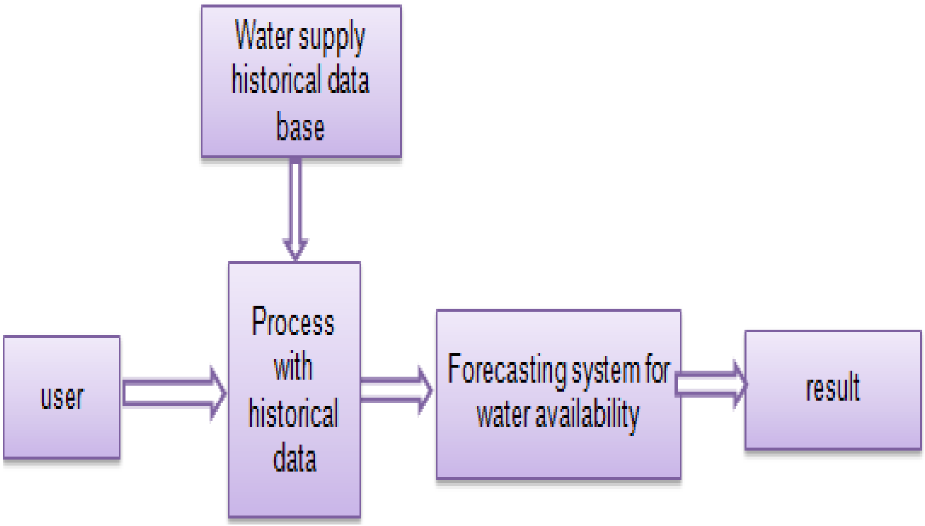
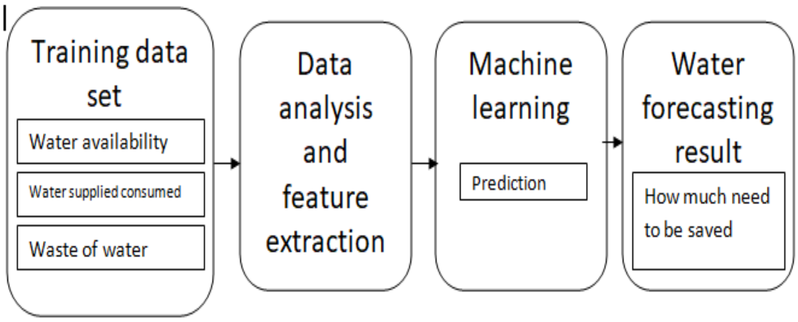


Fig.1. Model Frame

In above block diagram we are going to give user input and water supply historical data base for processing block which will process or forecast using some machine learning algorithm and this processed data is available for water forecasting then will get actual result.

IV. ARCHITECTURE DIAGRAM



Hardware and software requirement:

- **Hardware requirement**
- PC/Laptop(4GB RAM/Graphics card/Windows 10/7)
- **Software requirement**
- Pycharm/python

SUBLIME

V. LINEAR REGRESSION

The main goal of regression is the construction of an efficient model to predict the dependent attributes from a bunch of attribute variables. A regression problem is when the output variable is either real or a continuous value i.e salary, weight, area, etc.

We can also define regression as a statistical means that is used in applications like housing, investing, etc. It is used to predict the relationship between a dependent variable and a bunch of independent variables. Let us take a look at various types of regression techniques.

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Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. Linear regression makes predictions for continuous/real or numeric variables such as sales, salary, age, product price, etc.

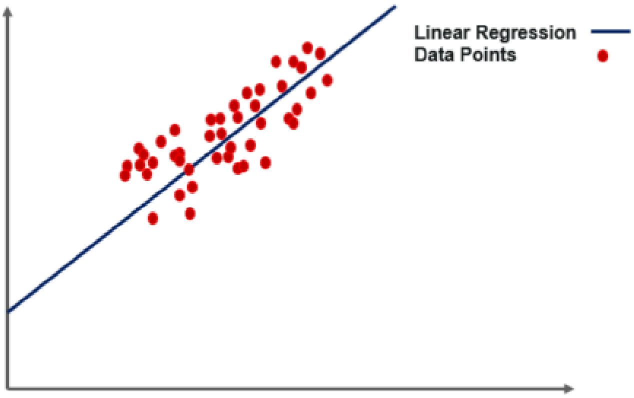
Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable.

Types Of Regression :

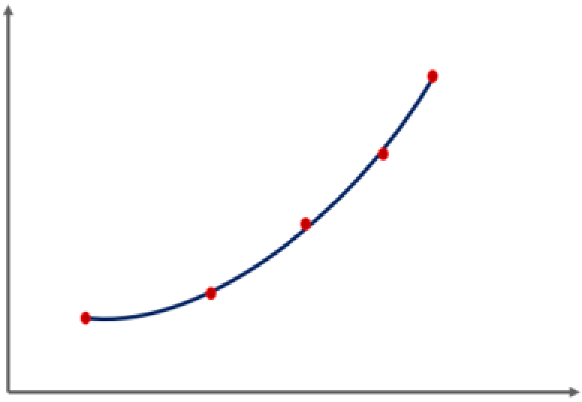
i. **Simple Linear Regression**
ii. **Polynomial Regression**
iii. **Support Vector Regression**
iv. **Decision Tree Regression**
v. **Random Forest Regression**

Simple Linear Regression:

One of the most interesting and common regression technique is simple linear regression. In this, we predict the outcome of a dependent variable based on the independent variables, the relationship between the variables is linear. Hence, the word linear regression.



Polynomial Regression:
In this regression technique, we transform the original features into polynomial features of a given degree and then perform regression on it.



Support Vector Regression:

For support vector machine regression or SVR, we identify a hyperplane with maximum margin such that the maximum number of data points are within those margins. It is quite similar to the support vector machine classification algorithm.

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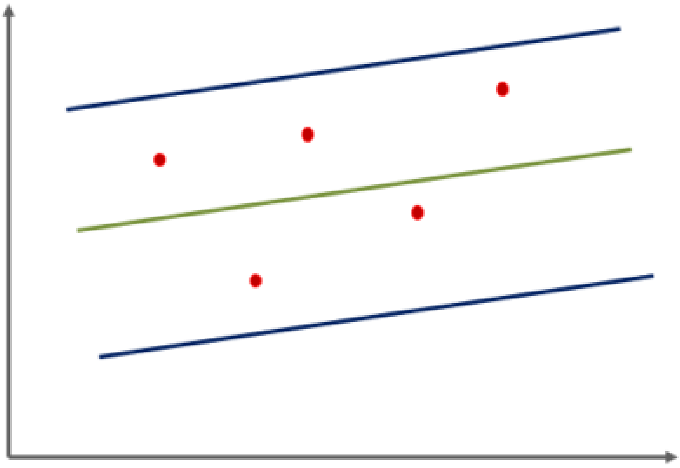

VI. CONCLUSION

Designing and implementing forecasting algorithms could save you up to 18% on your costs. When compared to previous methodologies, this research introduces automation water demand forecasting models that produce accurate prediction. It was proven to be reliable when applied to real-world water demand data, as long as the data used during training had no notable anomalies. In compared to the time serious approach (ARIMA) model, the machine learning method (SVM) proven to provide superior accuracy and efficiency when considering dapting a technique for water demand forecasting.

VII. FUTURE SCOPE

A large effort is currently underway in Kuwait to install smart metres in all Kuwaiti homes, which will provide more precise and diversified data. However, employing other machine learning and time serious techniques may yield better results than those produced in this study.

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