ISSN print 0716-0356
ISSN online 2452-5995
ISSN-L 0716-0356

TRILOGÍA

CIENCIA · TECNOLOGÍA · SOCIEDAD

ARTÍCULOS

UTEM
UNIVERSIDAD TECNOLÓGICA METROPOLITANA
del Estado de Chile

AGOSTO | 2023
Vol. 38 • Nº 49

Conference paper EVIC versión XVII, 2022

Ian Poveda
Universidad Tecnológica Metropolitana,
Santiago, Chile
Correo electrónico: ian.povedad@utem.cl

Diego Fuentealba
Universidad Tecnológica Metropolitana,
Santiago, Chile
Correo electrónico: d.fuentealba@utem.cl

Nicolás Ruminot-Ahumada
Universidad Tecnológica Metropolitana,
Santiago, Chile
Correo electrónico: nicolas.ruminot@ug.uchile.cl

Samuel Montejo-Sánchez
Universidad Tecnológica Metropolitana,
Santiago, Chile
Correo electrónico: smontejo@utem.cl

Artículo

SMART IRRIGATION THROUGH WATER CONSUMPTION: PREDICTION

RIEGO INTELIGENTE MEDIANTE EL CONSUMO DE AGUA: PREDICCIÓN

Recibido: 2 de diciembre de 2022 | Aprobado: 24 de abril de 2023 | Versión final: 25 de mayo de 2023.

Cómo citar este artículo:
Poveda, I., Fuentealba, D., Ruminot-Ahumada , N., Montejo-Sánchez, S. (2023). Smart Irrigation through Water Consumption: Prediction. Trilogía (Santiago), 38(49), 18-23. Santiago de Chile: Ediciones UTEM.

ABSTRACT

Irrigation is an important factor in agriculture, savingup to 50% when it is smart. This work addresses smart irrigation through an IoT prototype that uses a prediction model trained with secondary data to predict how much water to irrigate. The results showed that the best model is with TCN, achieving an R2 of 0.91 for 1 day and 0.86 for 7 days. This model is implemented in a functional prototype applied to mints that seeks to test its use in a real crop.

Key words: Irrigation, Machine Learning, Forecast, Evapo-transpiration, IoT

RESUMEN

El riego es un factor importante en la agricultura, cuando es inteligente ahornando hasta un 50%. Este trabajo aborda el riego inteligente a través de un prototipo IoT que utiliza un modelo de predicción entrenado con datos secundarios para predecir con cuánta agua regar. Los resultados mostraron que el mejor modelo es con TCN, alcanzando un R2 de 0,91 para 1 día y 0,86 para 7 días. Este modelo se implementa en un prototipo funcional aplicado a mentas que busca probar su uso en un cultivo real.

Palabras clave: Riego, aprendizaje automático, previsión, evapotranspiración, IoT

I. INTRODUCTION

Global warming has affected crops, creating a problem that has been addressed with the Internet of Things (IoT) [1][2]. Efficient irrigation and water management are crucial in agriculture, saving up to 10-50% of water when irrigation is smart [3]. In this paper, we propose an irrigation system with predictions of water consumption computed by Evapotranspiration (ET) through sensor data capture and knowledge transfer by environmental variables from nearby weather stations.

II. BACKGROUND

A. Crop Evapotranspiration (ETc)

ET is defined as the amount of evaporated and transpired water from a crop over a timespan. It is expressed in millimeters (mm) per unit of time and considers climatic variables such as temperature, solar radiation, wind speed, and humidity [4]. There are several ways to calculate ET, but the most widely used is through the Penman-Monteith equation (FAO56 PM) [4] defined as:

$$ET_0 = \frac{0.408\Delta\left(R_n - G\right) + \gamma \frac{900}{T+273} u_2\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34u_2\right)}$$

R_n is the total light radiation on the surface of the crop, G is the heat exchange flow in the soil, T is the environmental temperature of the site, is the wind speed,u_2 is the water vapor saturation pressure,e_s is the water vapor pressure, Δ is the slope of the water vapor pressure curve, and γ is the psychometric constant [4]. Then, the ET_C is ET_0 times a crop coefficient (K_c) [4].

B. Irrigation systems and forecasting methods

Irrigation methods typically use ET_C, calculated from K_c as the difference in soil moisture from day to day from IoT devices to determine how much to irrigate [1][2]. On the other hand, ET_C has been predicted using SARIMA time series, CNN (Convolutional Neural Networks), Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) [5][6][7]. The best forecasting method found is CNN, with an RMSE of 0.75 for a one-day horizon and 0.9 for seven days into the future.

III. METHOD

The problem addressed is irrigation forecasting for water saving in a crop. Scopus and WoS were searched on irrigation forecasting methods. This work has two stages: The former consists of searching for a model that can be fitted to an IoT prototype. The second stage consists of building an IoT prototype to use the predictive model in plant irrigation.

- Stage 1.- Model Assessment: Historical observed ET data and climatic variables such as temperature, humidity, wind speed, and solar radiation for model evaluation were obtained from agrometeorologia.cl. On the other hand, historical data of weather forecasted variables such as air temperature and humidity, wind speed, and cloudiness percentage were purchased from www.openweathermap.org. Finally, complementary data for the calculation of ET in the irrigation prototype, such as cloudiness percentage, was obtained free of charge from the OpenWeatherMap API. This data is used to test several models such as SARIMA, CNN, MLP, Linear Regression and TCN.

- Stage 2.- Prototype Construction: The automatic irrigation system uses a DHT11 air temperature and humidity sensor, three soil moisture sensors, a relay, a water pump, an Arduino MKR1000 and a Raspberry Pi. Python was used for programming the prototype and models.

IV. RESULTS

A. Model Assessment

The LR, MLP, and SVR models were trained with forecasted climate data, being the most accurate SVR with an R^2 of 0.92. On the other hand, SARIMA and CNN models were trained with historical ET data, being the most accurate CNN with an R^2 of 0.91. Table I shows a comparison of the models tested, where the most suitable model was the one built based on CNN - TCN (Temporal Convolutional Networks) with historical data.

Table I
Assessed Models

Dataset	Data Cost (GBP)*	Model	Forecast Horizon	R^2	NRMSE
Forecasted climatic data	40	LR	1 day	0.8	0.174
			7 days	0.8	0.240
		MLP	1 day	0.9	0.159
			7 days	0.8	0.230
		SVR	1 day	0.9	0.145
			7 days	0.8	0.230
ET data	0	SARIMA	1 day	0.6	0.300
			7 days	0.6	0.340
		TCN	1 day	0.9	0.160
			7 days	0.8	0.190

*Date 17-10-2022

Fig. 1 shows the prototype schematic, based on an Arduino system connected to a Raspberry Pi via WiFi. The application is based on Python, Keras-tcn, PyET, Flask, PostgreSQL as a database and Mosquitto MQTT for message exchange. The irrigation system runs two scripts, one in charge of managing the sensors and actuators and another one in charge of calculating how much to irrigate. Script 1 saves the data in the database and sends the irrigation signal via the MQTT. Script 2 calculates the ET of the day, the water consumption forecasts for the next seven days and communicates to script 1 that it should irrigate.

Fig. 2 shows the irrigation system implemented. (a), (b) and (c) show the three mints, each with a soil moisture sensor. In (e), the DHT11 sensor is located. In (d) is located the Arduino, in (f) is located the relay and in (g) is located the water pump connected to a water tank.

Fig. 1. Prototype Diagram

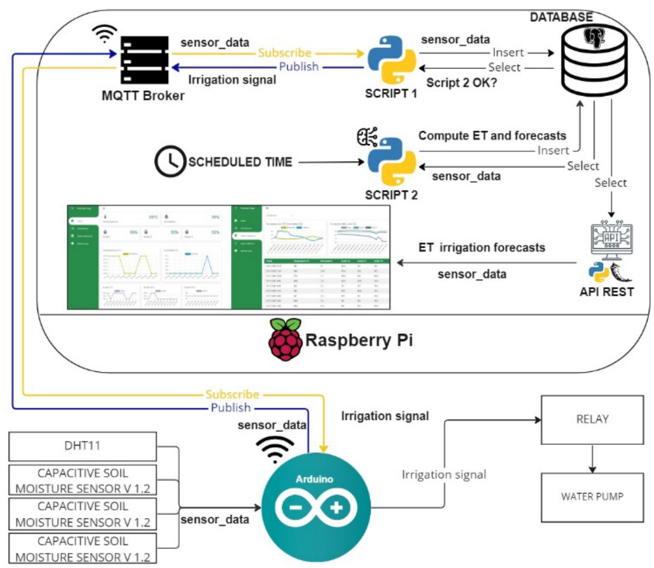
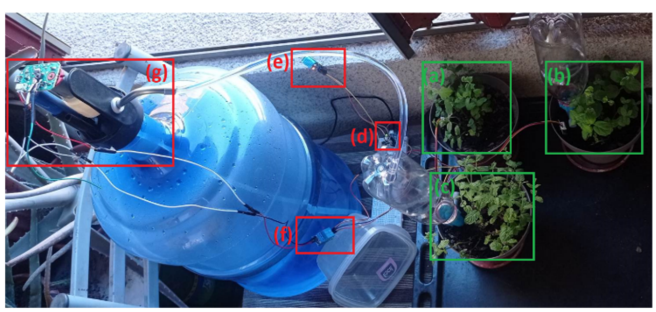


Fig. 2. Irrigation System



V. CONTRIBUTION AND FUTURE WORK

This work proposes a functional predictive irrigation prototype using machine learning from a previous evaluation of possible feasible models. Future work will consist of evaluating the quality of the predictive model that is initially trained with secondary data (Weather Stations) to be used with the prototype data. Another future work will be to analyze the behavior of soil moisture when applying different amounts of water over time.

REFERENCES

J. M. S. Baylon, D. L. Burgos, and J. B. G. Ibarra, “IoT-based Smart Irrigation System for Solanum Melongena or Eggplant using Evapotranspiration with Penman-Monteith Equation,” in *2021 IEEE 9th Conference on Systems, Process and Control (ICSPC 2021)*, IEEE, 2021, pp. 186–191.

M. V. Caya, A. Ballado, E. M. C. Rabino, and C. A. H. Delim, “ET-Based smart irrigation system with irrigation postponement algorithm for lycopersicon esculentum or tomato plant,” in *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, IEEE, 2019, pp. 1–5.

E. Bwambale, F. K. Abagale, and G. K. Anornu, “Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review,” *Agric Water Manag*, vol. 260, p. 107324, 2022.

R. G. Allen, L. S. Pereira, D. Raes, and M. Smith, “Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56,” *Fao, Rome*, vol. 300, no. 9, p. D05109, 1998.

P. de O. e Lucas, M. A. Alves, P. C. de L. e Silva, and F. G. Guimarães, “Reference evapotranspiration time series forecasting with ensemble of convolutional neural networks,” *Comput Electron Agric*, vol. 177, p. 105700, 2020.

S. Traore, Y. Luo, and G. Fipps, “Deployment of artificial neural network for short-term forecasting of evapotranspiration using public weather forecast restricted messages,” *Agric Water Manag*, vol. 163, pp. 363–379, Jan. 2016, doi: 10.1016/j.agwat.2015.10.009.

X. Jiang, W. Chen, and J. Shao, “Forecast of-reference crop evapotranspiration based on public weather forecast.,” *Journal of Drainage and Irrigation Machinery Engineering*, vol. 37, no. 12, pp. 1077–1081, 2019.

UNIVERSIDAD TECNOLÓGICA METROPOLITANA
UTEM
del Estado de Chile

TRILOGÍA
CIENCIA · TECNOLOGÍA · SOCIEDAD

EDICIONES UNIVERSIDAD
TECNOLÓGICA METROPOLITANA