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Intelligent Mechanisms for Irrigation Optimization via Treated Wastewater Management in Precision Agriculture—The AUGEIAS Example †

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Abstract: Access to clean water is vital to human health, communities' development, and economic prosperity. Nowadays, more than 10% of the global population lacks access to clean water. This has created the so-called "water crisis" and set, as a key goal for communities, the protection and optimization of water usage. In this direction, technological concepts, like internet-of-things (IoT) and artificial intelligence (AI) assisted recommendation, which enables real-time monitoring and efficient exploitation of water resources, have been identified as fundamental pillars of the solution. This inspired the design, development, and testing of several breakthrough concepts in this domain; however, to the best of our knowledge, none of them lies in real-time intelligent exploitation of mixing clean and recycled water for crops irrigation. Motivated by this, in this paper, we present a holistic next-generation IoT approach, namely AUGEIAS, for optimal clean and treated wastewater usage in precision agriculture. In more detail, we present AUGEIAS architecture and explain its features and functionalities. Moreover, the AUGEIAS intelligent mechanisms that allow accurate crops water demand and weather prediction, as well as optimization, are documented. Finally, the front end of AUGEIAS platform is presented.

Keywords: Internet of Things; low-power wide-area networks; long-range wide-area network; data integration point; open-data reliability; irrigation optimization

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1. Introduction

Water is a prerequisite for human well-being and agricultural production. The demand for freshwater resources is increasing, while the climate crisis has already intensified the water cycle, exacerbating flooding and drought [1]. Agriculture is responsible for about 65–75% of freshwater withdrawals used for irrigation [2]. Therefore, efficient water resource management is considered to be of outmost importance [3]. In a similar line of research, the exploitation of non-conventional water resources in order to minimize usage of freshwater resources (e.g., rain harvesting, treated wastewater) has attracted some attention [4].

Nowadays, precision agriculture has become an increasingly popular concept as a result of the advancement of the next-generation Internet-of-Things (IoT) technology. IoT in agriculture provides the ability to collect real-time information on the crops with the help of sensors, without human intervention, and monitor crop state and condition; on the other hand, big data analysis and Artificial Intelligence (AI) mechanisms allow for knowledge acquisition and predictions, assisting, therefore, evidence-based decision making and optimizing the production process (e.g., water use efficiency, water availability in terms of quality and quantity, crops quantity and quality, and minimization of usage of chemicals).

Scanning the technical literature, only a small number of papers that focuses on treated wastewater management in precision agriculture through the exploitation of internet-of-things (IoT) sensors—in order to minimize exploitation of water resources, usage of fertilizers, and consumption of energy so as to increase crop quality and production—can be identified (see, e.g., [5–8] and references therein). In more detail, in [5], the authors revisited and documented AI and IoT approaches that find application in precision agriculture, with emphasis on treated wastewater management. In [6], integration of a wireless sensor network was discussed, as well as a preliminary validation in a wastewater treatment plant scenario of a low-cost treated wastewater water quality monitoring device and management system in the close-to-market stage. In [7], the problem of sewer and stormwater monitoring across networked landscapes, water quality assessment, treatment, and sustainable management was documented, and IoT-based smart solutions were enumerated. Finally, in [8], the authors presented a decision support system (DSS) for conjunctive use of treated wastewater with groundwater in order to minimize irrigation water usage.

Despite their paramount importance and the attention that state-of-the-art treated wastewater management solutions have attracted, to the best of the authors' knowledge, no holistic approach that allows intelligent and autonomous treated wastewater, clear water, and rainwater mixing and management has yet been discussed. Motivated by this, in this paper, we present AUGEIAS ecosystem, exploiting in a cost-efficient, albeit safe way the usage of treated wastewater for wastewater treatment plants (WWTP), contributing to crop production improvement and environmental footprint minimization in terms of chemicals and freshwater usage. Specifically, an IoT system, comprising energy-efficient network protocols and a data management platform, and AI mechanisms were developed in order to collect, correlate, and predict the quality characteristics of treated wastewater and its effect on crop production. Finally, we present the pilot implementation of the project along with collected data visualization examples.

The rest of this paper is organized as follows: the data architecture of AUGEIAS is presented in Section 2; the intelligent mechanisms for irrigation optimization are presented in Section 3, and special emphasis is laid on evaluation of the reliability of open data that are exploited to improve prediction accuracy; the pilot site is presented in Section 4, and initial results and statistics based on the collected data are provided; a discussion about the AUGEIAS case and its contributions is presented in Section 5.

2. AUGEIAS Data Architecture

IoT network and data-management-related platform allow for collection, processing, and analysis of information from sensors deployed in the field and the WWTP. IoT data and open data that are also exploited in the context of AUGEIAS ecosystem are integrated in the cloud, while their reliability is estimated in order to improve crop water needs prediction mechanisms.

The rest of this section is organized as follows: Section 2.1 provides details of IoT network and designed energy-efficient communication protocol; Section 2.2 describes IoT data management platform developed for data collection from different sources, integrating different networking technological solutions; finally, Section 2.3 presents how IoT and open data is integrated into Amazon web services (AWS).

2.1. IoT Network

Long-range wide-area network (LoRaWAN) and narrow-band-IoT (NB-IoT) are the two most widely deployed and used low-power wide-area networks (LPWANs) [9]. LoRaWAN technology is attracting intense interest, owing to its long transmission range in suburban and rural environments, its inherent connectivity support for a large number of IoT devices and its low-energy consumption. In addition, it operates in the unlicensed frequency band for industrial, scientific, and medical purposes (ISM). Thus, LoRaWAN affords an easy and low-cost process, compared to other solutions in low-power wide-area network. In light of what has just been discussed, the AUGEIAS's smart ecosystem adopts the LoRaWAN, although its architecture could also support NB-IoT networks for the transmission of IoT-devices data.

Different types of IoT devices can gain access to the IoT network through gateways (GWs), as depicted in Figure 1. In the uplink, the GW forwards the collected data to the Gateway Server (GS), which routes the packets to a predefined network server (NS). At the downlink, the GS forwards medium access control (MAC) level commands to the GW, as well as messages containing resource usage information. The GS is responsible for routing information and commands from the gateway to the network server and vice versa. Finally, the NS forwards the received data to the application server (AS). An experimental testbed for AUGEIAS has been developed where a Smart Environment Pro Libelium Sensor System with temperature, precipitation, and CO concentration sensors [10] is connected to one LoRaWAN gateway, which, in turn, is connected to the LoRaWAN network and application server implemented in chirpstack platform [11,12].

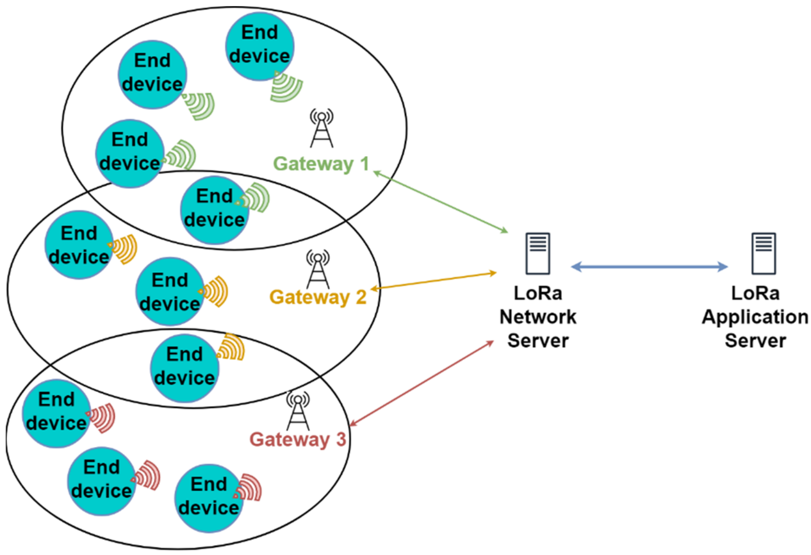

Figure 1. AUGEIAS LoRaWAN topology.

Due to limited computational, communication, and energy resources imposed on IoT devices, data rate and energy efficiency need to be carefully balanced in order to maximize throughput, while prolonging the network lifetime. In this direction, the selection of the communication protocol constitutes a determinant factor of the network lifetime and the overall performance of LoRaWAN systems. Motivated by this and considering deployment of GWs in the field empowered by solar panels, a green, robust, and resilient communication protocol, called GreenLoRaWAN, is presented in [13]. GreenLoRaWAN increases energy efficiency, scalability, and robustness of the system, while preventing the failure of the network caused by depletion of energy resources. It is a suitable solution for systems in harsh environments that cannot ensure a continuous power supply from the electricity grid. GreenLoRaWAN allows IoT devices to be associated with a single gateway at both the uplink and the downlink, taking into account the energy resources of each gateway at the time of association. As opposed to the star-of-stars topology of LoRaWAN [14] and prior related research (e.g., [15,16]) that describes IoT devices being served by a single gateway only in the downlink transmission, GreenLoRaWAN considers that sensor measurements are forwarded to the NS only by the associated GWs, minimizing resource consumption and associated transmission costs, while also relieving NS from removing duplicate packets received. Initial simulation results that were acquired showed that the proposed association enabled energy saving on the network's GWs and on the overall access network, which, in turn, increased network lifetime. As future work, we consider usage of sectorial antennas on end devices in order to minimize collisions and energy consumed during packet reception at GWs.

2.2. IoT Data Platform

AUGEIAS IoT data platform allows for IoT data collection to consider both LoRaWAN and NB-IoT networking technologies. Additionally, data from external systems and open data could also be integrated. As illustrated in Figure 2, in the AUGEIAS platform, there are three identified data-generation scenarios. Specifically, in scenario A, sensor data are communicated via NB-IoT to a GW and then to a proprietary platform, which then transmits them in javascript object notation (JSON) format to the platform, while, in scenario B, sensor data are transmitted via LoRaWAN to a gateway and then to an IoT server. An IoT server is a software package that manages IoT data packets for open protocols, such as LoRaWAN, and may be hosted on an open server, like broker or online solution. As already mentioned, first, data are forwarded to the GS, then to the NS, and finally to the AS. The AS formulates the data in a JSON format and forwards them to the AUGEIAS platform. Lastly, in scenario C, open data, such as meteorological data (e.g., temperature and humidity) or data from external systems may be pulled in JSON format for correlation with sensor data.

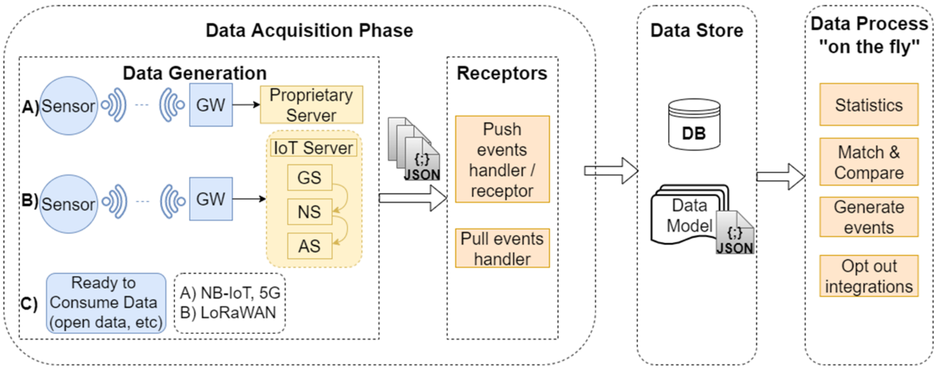

Figure 2. AUGEIAS platform architecture.

The appropriate receptors have been developed to receive the data based on its type, as depicted in Figure 2. The AUGEIAS platform supports two kinds of mechanisms to integrate new sources of data, namely the (i) push and (ii) pull mechanisms. The push mechanism is a hypertext transfer protocol (http) endpoint that concerns the sources that push their data (e.g., http integration from an AS), whereas the pull is a periodic mechanism, which pulls data from the sources that expose their data through an application programming interface (API), such as open data. Then, there is a data consolidation point, where all the collected data are stored for further processing. At this point, the AUGEIAS platform user can filter and select the data to be stored on the platform, as well as defining the data model. Additionally, the platform displays statistics based on user-configured data models. Another functionality that the user can perform is matching and comparing data to check if specific conditions and/or requirements are satisfied (e.g., check if a temperature value is greater than, less than, or equal to a value) and, as a response, generate events (e.g., send a notification or perform an action from the platform based on the result acquired). Finally, the platform supports opt-out integration, which is the http out that creates a post request to a given destination to forward the data to third-party applications or alerts after an automation is created.

2.3. Amazon Web Services Integration

Cloud computing technology enables flexible, on-demand network access to a shared set of configurable computing resources (such as networks, servers, storage, applications, and services). There are several cloud computing platforms like Microsoft Azure, AWS, Google Cloud, IBM cloud, and Oracle Cloud infrastructure. In AUGEIAS, the collected

IoT data from the field and WWTP are forwarded to an Amazon elastic compute cloud (Amazon EC2) instance on AWS cloud [17], and are integrated with open meteorological data retrieved from several open sources. Specifically, an Amazon EC2 M5 Instance [18] is initiated, in which InfluxDB is installed for storing time series non-structured data [19]. Several tools such as Telegraf and Grafana are also installed on the initiated VM [20,21]. Telegraf is a data collection agent, which collects data from external data sources and stores them on InfluxDB. Then, from InfluxDB, the stored data are sent to Grafana open-source software for query execution, visualization, and notification generation. It converts collected data from sensors (either real-time or stored) into graphs, enabling direct comparison of time series data in order to draw important conclusions on the state of a system with the ultimate goal of improving its operation. AWS Cognito is used to manage user identities and access control for the AUGEIAS website based on predefined roles. AWS QuickSight is a cloud-based business intelligence service that makes it easy to build visualizations, perform ad-hoc analysis, and quickly get business insights from AUGEIAS data.

3. Intelligent Mechanisms

The key objective of AUGEIAS intelligent mechanisms is to optimize irrigation through data analysis and AI enabled predictions for assessing crop needs, the risk of using treated wastewater for irrigation based on its quality characteristics, as well as weather forecasts, in order to provide suggestions to end users (e.g., proper mixing ratio of freshwater and treated wastewater, dynamic pricing of treated wastewater) and create automations. Thus, AUGEIAS ecosystem implements an integrated decision-making mechanism, which takes into account the data from the open APIs and the sensors installed in the field and WWTP, additional parameter values after laboratory analysis (e.g., leaf analysis), the relevant legislation and models of plant/crop growth and introduces them into machine learning (ML) algorithms, which provide recommendations for optimizing production.

As illustrated in Figure 3, AUGEIAS ecosystem implements a quality assessment engine to evaluate the quality characteristics of treated wastewater, so as to estimate the risk of its usage in crops/environment and determine an appropriate mixing of treated wastewater with conventional water, considering the safety threshold set by legislation, refined after assessing potential impact of its use on crops (quantitative/qualitative change). Finally, a dynamic treated wastewater pricing algorithm is developed, which considers current demand and quality characteristics of the treated wastewater, as well as international pricing practices. In the following subsections, we elaborate on the open data reliability estimation and discuss on the way open data are exploited in the AUGEIAS ecosystem.

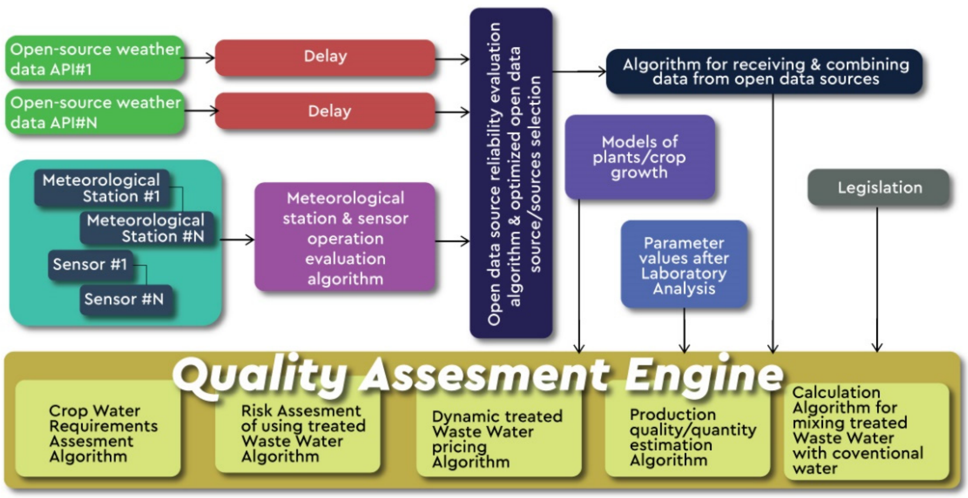

Figure 3. Architecture and structural subsystems of AUGEIAS smart ecosystem.

3.1. Open Data Reliability

Weather forecasting is an important scientific field, and various methodologies have been used in order to facilitate forecasting based on either statistical or machine learning time series analysis. Statistical analysis is usually applied by an autoregressive integrated moving average (ARIMA) model. In this approach, input data are considered to be stationary, and, as such, the method is more appropriate in linear applications [22]. On the other hand, ML models can be implemented in order to tackle the problem of weather forecasting, such as multi-layer perceptron (MLP) [23] or recurrent neural networks (RNN) [22–25]. However, MLP takes a long time for convergence, depending on the initial values and applied minimization algorithm [23], while feedforward neural network (FFNN) does not account for the previous data, which are important in weather prediction [22,23].

As an alternative, long short-term memory (LSTM) networks may be utilized [25]. LSTMs are an extension of RNNs, which exploit feedback connections that can process not only single data points, but whole sequences of data. The general approach is a multi-stage workflow that includes data fetching, data cleaning, feature engineering, model training, and evaluation [25]. The selected activation function and weight initialization play a crucial part in model performance [23]. The models discussed in the bibliography use either a multivariate dataset of weather variables—such as minimum and maximum temperature, minimum and maximum relative humidity, wind speed, sunshine, and evapotranspiration—or a univariate dataset in order to predict a single target variable that can be rainfall or visibility. Results are encouraging, as these networks show to be more skillful by measuring their root-mean-square deviation (RMSE) [23,24], which is the standard in measuring model performance, compared to statistical models and FFNNs. Multivariate datasets, or datasets with intermediate variables, such as dew point, provide better results [24] compared to single-variable datasets. Limitations of LSTMs include data availability (or lack of), imputation of missing values, and incorporation of dependent weather variables.

AUGEIAS ecosystem, in order to evaluate data reliability from open data sources (weather data), proposes a machine learning model based on LSTM networks, as shown in Figure 4. For each available dataset, mean absolute percentage error (MAPE), as a ratio between the actual value from the meteorological station that is installed in the field and the value that the dataset provides, is calculated. Data, after enrichment with the value of MAPE for each target variable, will be used as input in order to train a LSTM. The ML network topology, which is a work in progress, will be determined by the complexity of the data and the number of input and output neurons. The ML network, after the necessary training, will be applied to predict new values for the target variables, including their accuracy scores, in order to enhance the accuracy of the forecasting dataset. At the following step of the algorithm, the calculation of a weighted linear sum utilizing the predicted data will determine the best dataset to be used in conjunction with a K-nearest neighbors' algorithm in order to produce the best values that are fed to the irrigation optimization ML algorithm.

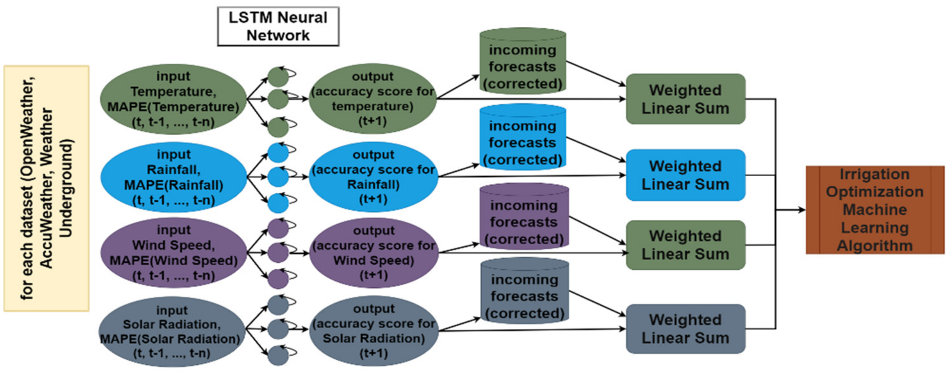

Figure 4. AUGEIAS machine learning model based on LSTM networks.

3.2. Irrigation Optimization

One of the main goals of the AUGEIAS ecosystem is to optimize usage of irrigation water, both by meeting the needs of the crop and by saving the available water resources, while also minimizing the environmental footprint. To calculate the crop requirements concerning irrigation, the Peyman–Monteith model is used, which is based on finding the crop evapotranspiration [26]. Utilizing the estimated crop water requirements and the weather forecasts, based on open sources data acquisition and their reliability, predictive irrigation mechanisms will be implemented in order to optimize the management of both conventional and treated wastewater.

4. AUGEIAS Pilot Case

The pilot case was implemented in a field located near the Municipal Enterprise for Water Supply and Sewerage in Kozani (DEYAK) WWTP, in north-western Greece, near the city of Kozani. Specifically, the field was divided into three areas. The first area of the field concerned the part that was irrigated through treated wastewater as retrieved from the WWTP, the second area was irrigated through conventional water, while the third part was not irrigated. Sensors were employed in each area to monitor weather conditions, soil conditions, and quality of the crop. In more detail, in the first part of the field, a station was installed, consisting of a meteorological station, a system for measuring soil parameters (e.g., temperature, conductivity, moisture), and an NDVI measuring system. In the part of the field irrigated with conventional water, a soil sensor that measured soil volumetric water content (VWC), temperature, and bulk electrical conductivity (EC_b) was installed. Finally, in order to better serve the needs of the project, an additional agrometeorological station was also installed in the non-irrigated area of the field. This station measured: air temperature, relative humidity, precipitation, windspeed, and leaf moisture, as well as soil salinity, humidity, and temperature at three different depths (5, 15, and 25 cm), respectively. Considering the quality characteristics of the treated wastewater in the exit of the WWTP, temperature, specific conductivity, rugged dissolved oxygen (RDO), turbidity, pH, oxidation-reduction potential (ORP), total Coli, biochemical oxygen demand (BOD), chemical oxygen demand (COD), nitrate (NO_3), and chlorine were measured.

Regarding weather forecasts, open weather data sources considered include OpenWeatherMap (3 stations), One Call API (Dark Sky), AccuWeather, and Weather Underground weather platforms. Weather forecasting data were correlated to those recorded by the agrometeorological station installed, in order to estimate their reliability. Error calculation for each API was performed using MAPE, and the obtained results displayed that all APIs provide efficient forecasts. However, OpenWeatherMap was the most reliable source, with an efficiency rate of 83.3% (average error 16.7%), followed by AccuWeather with 82.7% (average error 17.3%), and, finally, Weather Underground with 82.5% (average error 17.5%). The values for each target variable calculated through the MAPE were used as input in order to train a LSTM, as described in Section 3.1.

Figure 5 provides a visualization of the data from the APIs and the agrometeorological station using Grafana. Forecast and actual data are graphically displayed in a single dashboard, making it easy to compare and present them to stakeholders.

Figure 5. Dashboard with data from APIs and the agrometeorological station in Grafana.

5. Discussion & Conclusions

Utilizing IoT technology and exploiting current advancements in LPWAN and AI-related mechanisms, AUGEIAS aims to optimize irrigation in precision agriculture, considering usage of treated wastewater. In this context, data collected from sensors installed in the field and WWTP were exploited, while also considering open data and data available from external systems after assessing their reliability along with additional parameter values, relevant legislation, and models of plant/crop growth, introducing them into machine learning (ML) algorithms and AI-based intelligent irrigation mechanisms. AUGEIAS intelligent water quality assessment and irrigation optimization engine will predict future requirements concerning both treated wastewater and conventional water, estimate the risk of using treated wastewater for irrigation purposes to define the proper mixing ratio required for irrigation, and estimate its effect on crop production. Finally, the pilot site is discussed, presenting the sensors installed; as far as data collection is concerned, an energy-efficient LoRaWAN protocol has been proposed and an IoT data management platform implemented, integrating data from both LoRaWAN and NB-IoT networks.

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