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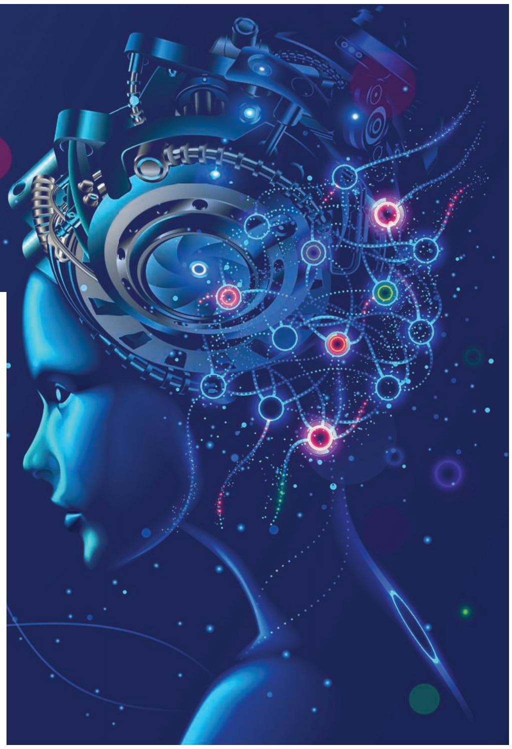

AI for Water

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Water availability is a prerequisite for flourishing economies, protecting public health, and national prosperity. An overview of the potentials of artificial intelligence for water is presented.

In the United States, there are about 153,000 public drinking water systems[1] and more than 16,000 publicly owned wastewater treatment plants.[2] While systems control and data acquisition (SCADA) has become a standard in large water treatment and distribution plants,[3] a very small (unknown) percentage of those plants have cyber defenses in place.[4]

MOTIVATION

SCADA infrastructures, as evidence shows,[5] are very prone and vulnerable to cyberthreats. Additionally, there has been a rising number of attacks, especially on water plants, in the United States and around the world. The traditional cybersecurity approach to utilizing firewalls and double authentication is beneficial and can mitigate multiple forms of cyberattacks; however, more sophisticated attacks, such as data poisoning, data manipulation, minimum perturbations, concealed attacks,[6] info stealer, botnets, and ransomware, require algorithms that can detect unusual activities (that is, outlier events)[7]; classify the source of adversarial actions; and perform attack mitigation activities. The current state of the art provides evidence that artificial intelligence (AI) is the leading approach to such defenses[8] due to its ability to adequately identify unwarranted pattern shifts in networks and datasets, a feature that is not achievable using traditional approaches.

STORIES OF INTEREST

Critical infrastructures, such as smart grids, nuclear plants, medical monitoring systems, smart farms, and intelligent water systems (IWSs), are deemed obsolete (and dangerous to human life) without comprehensive measures to protect them and secure their outcomes.[9] The workings of these systems are usually governed by laws and policies as well as domain-specific best practices.[10] However, the challenge of securing those cyberphysical systems is exacerbated by the dependency of their cyber, human, biological, and physical components on each other. For instance, a programmable logic controller controlling the pH levels of water at a treatment plant is an example of a cyber and bio interdependency; smart sensors reading water flow in municipal water pipes is an example of physical and cyber

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dependencies; and so on.[11] Wastewater treatment plants dump treated water (effluent) into rivers all over the country, while U.S. Environmental Protection Agency policies dictate acceptable amounts of phosphorous and nitrogen. For instance, an unwarranted modification of that value as being measured by sensors at a wastewater treatment facility can cause severe environmental damage to rivers and lakes due to excess amounts of such chemicals—that is not hypothetical; recent motivation examples of applying AI for water are presented.

Data poisoning and water poisoning

In the last two decades, U.S. water systems have been exposed to different cyberthreats.[12] In 2015, the U.S. Department of Homeland Security responded to 25 cyber incidents related to the water sector, representing a 78.6% increase in the number of reported cases since 2014[2]—one of the highest rate increases among all sectors. Cyberattacks have continued to grow exponentially relative to the attention given to the sector by governments, operators, practitioners, and academics—deeming the sector unsafe.[13] In February 2021, a plant operator in Oldsmar, FL, saw his cursor being moved around on a computer screen, starting various software functions that control the water being treated. While the operator assumed that it was another employee accessing the system remotely, the intruder boosted (that is, data poisoning) the value of one data point—the sodium hydroxide (lye) amount—by 100 times. Sodium hydroxide, the main ingredient in cleaning liquids, is added to treat the acidity of water and remove metals from water for purposes of human consumption (that is, drinking). Increasing its amount to higher levels can cause poisoning, burns, and multiple other health risks.[4]

Water, farmers, and irrigation

The Brookings Institution reports an average of 30 farmers committing suicide per day in India due to water-related events.[14] Albeit this is a fluctuating rate, the cause of farmers' uncertainty is increasingly due to water access, extreme weather events, rainfall, the lack of water, inaccurate forecasts of water levels in rivers and lakes,[15] and unwarranted chemicals in water used for agricultural irrigation. Such events affect agricultural yield, the quality of crops, crop disease, and even the prices of agricultural commodities around the world.[16] As is known, nimble agriculture and food security is vital to human survival. In the past three years, global agriculture has been negatively affected by many water-related shocks. Unprecedented uncertainties (such as floods and droughts) have affected the range of decisions starting at the farm and reaching the household consumption of certain goods.

Water Security

We suggest that the status quo definition of *water security* ought to expand from merely covering water "availability" to including cyber-, physical, and biosecurity aspects.[17] Conventional definitions don't satisfy the rising need to cover all areas of how water can be secure. The United Nations provides a working definition for water security as follows[11]: "Water security is defined here as the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods." Based on the three-pillared challenge involved in the sector (cyber, bio, and physical), we propose the following new definition for water security encompassing emerging trends and conventional challenges related to water availability and quality:

> "Water security is the capacity of nations to safeguard the quality and availability of water for all desired purposes of society, which includes ensuring measures related to securing access; valid treatment processes; cyber hygiene; and mitigating risks associated with environmental factors, data collection, biological threats, and emerging technologies."

While we understand that this definition is debatable, the goal of presenting such a definition is to urge scientists and practitioners in the water sector to consider the novel aspects.

AREAS OF APPLICATION

Water has an obvious effect on economies besides farming and drinking water. Societies flourish next to water bodies[18]; sanitation and health[19] are not manageable or possible without access to water; and manufacturing is heavily dependent on reliable water sources. It is rather difficult to capture all potential AI applications in the water sector; here, a brief review of three examples is elaborated.

Water treatment and management

As AI becomes more developed and deployed further across critical infrastructure, operators will be blindsided if they rely only on their past experience or expertise when making decisions (such as deciding on the number of pumps to operate during a storm, assessing the performance of the adsorption process, and evaluating water quality). Future leaders need to possess a fundamental knowledge of AI to better lead and protect their institutions.[20] A modern water treatment plant, referred to as an *IWS*, has hundreds of sensors and actuators—for pipes, tanks, reservoirs, and pumps. Such equipment has inter- and intradependencies that increase the complexity of detecting a breach.[21] Accordingly, AI can be used at wastewater treatment plants for multiple use cases in decision making.[22] Decision-making support involves optimization techniques to allocate an optimal combination of factors that maximize/minimize a numerical objective function (that is, the factor affected by the decision). From the onset of hydraulic modeling, optimization techniques have been critical to water distribution networks.[23] Areas of application that can benefit from AI optimization algorithms include: optimizing energy consumption, the number of pumps used at a certain point in time, the optimal design of monitoring and control networks, and the management of tunnels and pipes during extreme weather events.[24]

Optimization through AI is performed via multiple approaches, but the most common ones include genetic algorithms (GAs), deep learning (DL), and reinforcement learning (RL). For instance, if a water treatment plant aims to minimize nitrogen in the effluent, then a DL or GA optimization approach could be utilized. RL algorithms can, for instance, reinforce practices that lead to better water quality or increase water volume (gallons) processing per day.

Agricultural irrigation and farming

Essential crops (such as wheat, corn, and soybeans), livestock, fruit, and all agricultural commodities require water to survive. However, access to water is not always guaranteed; for instance, in drought-prone areas, smart irrigation is a critical strategy due to the scarcity of water.25 Urban and vertical farming are similar; in those scenarios, precision irrigation is important to maintain farm finances and create profit for the farmers.[16] Such AI-driven decision-making processes (for example, crop yield prediction, livestock price forecasting, and optimizing the right mix of biodegradable pesticides) are heavily dependent on big data. Data, however, are prone to poisoning, validation issues, and incorrectness. Poisoned data can change farming recommendations; manipulate smart-irrigation systems' outcomes; and compromise water meters, humidity sensors, water pumps, and other agricultural control devices.

Water economics and policy

Water and the environment are difficult spaces to regulate, mainly due to the shared nature of their resources (that is, the tragedy of the commons). Policymakers need to refer to experts to understand the domain and create reasonable policies that can govern the space fairly. Park et al.,[26] for instance, utilized AI, Shapley Additive exPlanations (SHAP), and partial dependence plots for identifying important variables that affect algal bloom in rivers: generally, a challenging (and potentially subjective) aspect to measure. One of the theories in computational quantification is referred to as *value loading*.[27] It presents matters with a subjective concept, such as policy evaluation—of the Clean Water Act 33 U.S.C. §1251 et seq. (1972), for instance—that could be defined mathematically and measured in a more empirical manner.

However, we argue the following for the application of AI for public policy. Science used as a foundation for statutes is ever changing, and in many cases, different contexts could lead to different results. Accordingly, data-driven lawmaking has to be one of the major ways of constructing and evaluating the success of statutes—a direction that is becoming progressively inevitable and is also increasingly further backed up by the public.[28] One of the ongoing debates in water and environmental law is the Water of the United States issue—that is, which authority (state versus federal) prevails and who has control over water bodies of the United States.

Multiple administrations have tackled this issue, but what is very interesting is the involvement of different scientific assumptions as a basis for criteria that define answers to the debate. For instance, the Obama administration used the significant nexus test, while the Trump administration used the narrower definition derived from the Supreme Court's Rapanos versus USA case, 547 U.S. 715 (2006). Both are deemed reasonable, but one would ask: Which one should be followed? And without sufficient data, how does one measure the outcome? The answer lies in empirical evaluations and scientific experimentation (not expert opinions or political partisanship)—multiple research institutes produce research that generates results and directions that ought to support a certain direction, although contradicting in some cases, but referring to such scientific debates usually leads to a consensus that is backed up by different dimensions.

In some cases, U.S. law cannot be defined in isolation; therefore, the national well-being also has to be in the balance when it comes to ratifying statutes that contradict or confirm international treaties. For such difficult goals to be balanced in the same legal realm, AI can be one of the main referees in determining the best version of a statute as it is being crafted or amended.

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AI has been helping cure disease, create art, drive cars, perform surgery, and identify crime; the water sector is no different. In this article, the use cases, AI methods, and applications aim to encourage the water industry to investigate and further apply AI for decision making while considering assurances (such as security) for deriving actionable intelligence.

Besides cybersecurity, explainability, and correctness, other challenges involved with AI's deployability to the water sector include adoption by operators; the black box nature of AI models; and data privacy issues—all of which are applicable to most sectors. Ultimately, however, these issues ought to be addressed, especially because water has no substitute. ■

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