Business Overview

WEO Inc.

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Ownerships:

1. Ms.Azadeh Shirvani Boroujeni (CEO),
2. Mr.Saeed Hamta (Managing Director),
3. Mr.Saeed Norouzi (Chief Technology Officer),
4. Mr.Morteza Mollazainali (General Manager),
5. Mr.Mohammad Hassan Alizadeh Nazmi (Director of Operations)

Business Descriptions:

WEO Inc., which will operate under as a Numbered Company Incorporated under the Province of Manitoba, will develop and distribute the Proprietary software applications for Waste Water Process Optimization purposes. Provided all goes to plan, the commencement of operations is scheduled on October 1, 2020. Our apps are estimated to reduce energy costs by 16.7% and alarms by 97%. Besides, the reduction of Carbon footprint will be in alignment with the Energy optimization, reduction in water &, and organic waste delivery schedules. Also, we provide a solution to save costs for the facilities by reducing the human intervention aspect of monitoring and attending to pumps, monitors, and alarm. The Data-driven solution is intended to convert, idle data, into a positive cash saving solution for the Wastewater Treatment companies in Manitoba, and to other Provinces in Canada.

Our Solution: SCADA, in conjunction with Artificial intelligence (AI) through Machine learning (ML), combination with IoT. Our proposed predictive control can anticipate the incoming Wastewater intake rate (WWIR) and to adjust the reservoir buffer accordingly. We are introducing a two-stage framework using ML, Learning Stage, and Operational Stage

The average WWIR primarily relies on the period of the year or day. Initially, during the first stage, initial learning of the control policy takes place. Forecasting WWIR based on fuzzy logic is the first step.

WWIR forecasting is effective in WW and drought management. For forecasting WWIR regression, we used Fuzzy logic

We use the adaptive neuro-complex-fuzzy inference system (ANCFIS) architecture; For general multivariate time series forecasting, multiple-input-single-output (MISO) networks are used.

Business Goals

Previous Data containing information about the pump's active power and frequency, the wastewater tank /reservoir level, WWIR, and outflow rate are collected from the SCADA system of the WWPS.This historical data is used for:

- WWIR probabilistic forecasts;
- Create data-driven models that emulate the physical environment;
- Set up episodes are combining historical data and forecasts.

Summary

1. Waste Water Treatment = Physical + Chemical + Biological => Highest Energy Consumption in Municipalities
2. Water Treatment Industry:
    a. WWTP
    b. DWTP
    c. WW Pumping
    d. DW Pumping
3. Chances:
    a. Reduce Energy Utilization
    b. Lower Electrical Peak: Savings Opportunities such as load shifting and self-generation
    c. Lower GHG Emission (CO2) while Biogas Recovery
    d. Lower Cost: Oil consumption Optimization
4. Two Targets of our project:
    a. WWTP Energy Consumption
    b. Carbon Emission
5. Current solution: WWPS operate with fixed level control rules:
    a. Math modeling tech : Not Optimized => Activated Sludge Models (ASM1,…ASM3): 13 Nonlinear Equations with 19 parameters which are not estimable
    b. Timetables: no measurement of the real incoming load and process state is done
    c. SCADA: Supervisory Control And Data Acquisition : Nearly all the control actions are automatically performed by the remote terminal units (RTUs) or by the programmable logic controllers (P.L.C.s)
6. Scada SWOT:
    a. Production and performance data is close to real-time, transported digitally, and can be accessed and executed remotely
    b. premise-based, requires extensive training and reliance on system providers almost totally. SCADA needs specialized industrial VPN and firewall solutions for SCADA networks that are established on TCP/IP. CYBER SECURITY!
7. Our Solution: SCADA, in conjunction with Artificial intelligence (AI) through Machine learning (ML), combination with IoT. Our proposed predictive control can anticipate the incoming

Wastewater intake rate (WWIR) and to adjust the reservoir buffer accordingly. We are introducing a two-stage framework using ML, Learning Stage, and Operational Stage

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11. Previous Data containing information about the pump's active power and frequency, the wastewater tank /reservoir level, WWIR, and outflow rate are collected from the SCADA system of the WWPS This historical data is used for :
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Problem

The Wastewater Treatment Industry is a mixture of various intricate series of biological, physical, and chemical processes that are used to treat and remove contaminants or pollutants from wastewater or sewage. Water treatment represents the most significant energy use for most municipal governments, according to Posterity Group Research. There are four segments in Water Treatment Industry, comprising Wastewater Treatment Plants (WWTP), Drinking Water Treatment Plants (DWTP), Wastewater Pumping stations (WW Pumping), and Drinking Water Pumping stations (DW Pumping). There are many chances to reduce energy utilization, lower electrical peak needs, and decrease Greenhouse Gas (GHG) emissions in water treatment sectors. The effective operation of wastewater treatment plants (WWTPs) is vital to make sure a sustainable and friendly green environment is maintained. Annual GHG emissions in the water treatment segments are approximately 0.58 Mt $CO2e$. WWTPs correspond to most of these emissions (46%), with a footprint of 0.27 Mt $CO2e$ (Posterity Group Research). The Co2 emissions arising from water and wastewater transport and sub-optimal treatment is also a concern. An analysis of electric energy intake, specifically, shows the most dominant energy end-utilization in the water treatment sectors is pumping, signifying 1.9 TWh, with 65% of all energy use.

Validation of the problem

Two main issues addressed in our project are

1)Energy consumption by Wastewater treatment process and

2) Carbon emissions caused by the process.

For many years in the United Nations (UN), wastewater treatment has been one of the significant objectives to guarantee the sustainability of the natural environment. The wastewater treatment plant is not only one of the vital electrical energy consumers, but it also consumes supplies of fossil fuel and coal and releases Greenhouse gases. Overall control of energy will have a positive knock-on effect in controlling costs and greenhouse emissions.

Our Solution

Our solution to this challenge will enable a decrease in energy use and energy costs; Lower peak demand, and Diminish Greenhouse Gas (GHG) emissions within the context of the Waste Water Treatment Sector. Our proposed predictive control can anticipate the incoming Wastewater intake rate (WWIR) and to adjust the reservoir buffer accordingly. We are introducing a two-stage framework using ML, Learning Stage, and Operational Stage

Learning Stage

We train the model on an emulated environment, constructed with supervised learning (SL - initial learning stage). The average WWIR primarily relies on the period of the year or day. Initially, during the first stage, initial learning of the control policy takes place. Forecasting WWIR based on fuzzy logic is the first step.

TIME series are observations recorded sequentially over time, such as Environmental Sensor Data, and historical Wastewater Intake Rate (WWIR). They are an important subcategory of data streams in which the data is not only temporally ordered, but the exact time of observation is also recorded (explicitly or implicitly). As mentioned before, we need to forecast the amount of optimal WWIR Forecasting time series is a significant machine learning problem. WWIR forecasting is effective in WW and drought management. For forecasting WWIR regression, we used Fuzzy logic. The term fuzzy refers to things that are not clear or are vague, and “fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false."[1]

We use the adaptive neuro-complex-fuzzy inference system (ANCFIS) architecture; For general multivariate time series forecasting, multiple-input-single-output (MISO) networks are used.

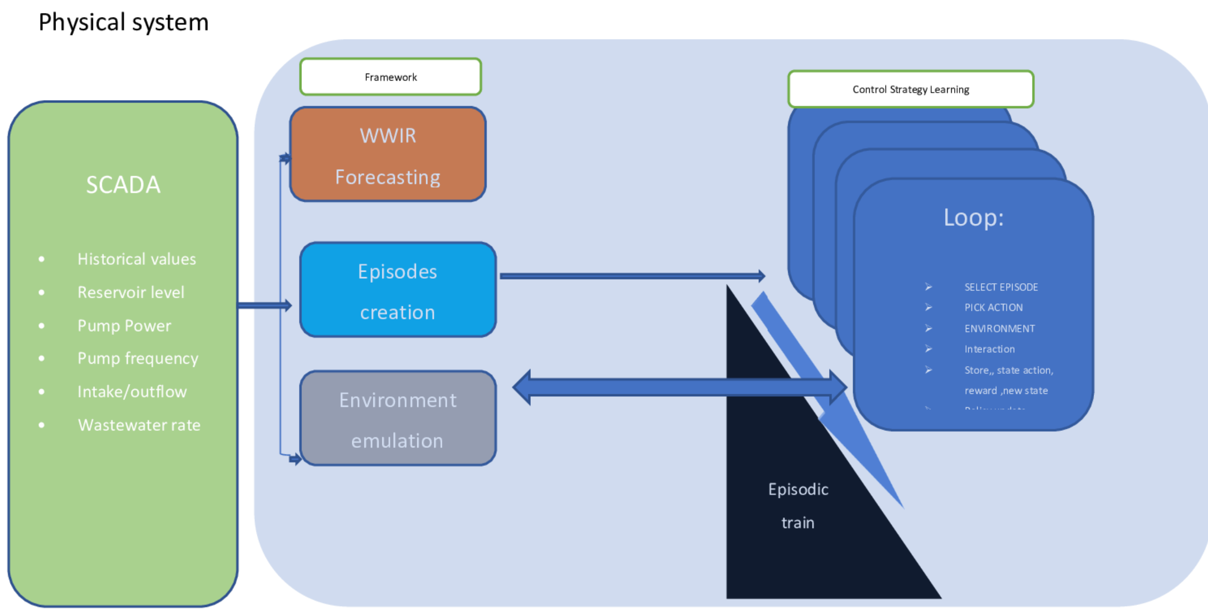
Previous Data containing information about the pump's active power and frequency, the wastewater tank /reservoir level, WWIR, and outflow rate are collected from the SCADA system of the WWPS This historical data is used for :

(i) WWIR probabilistic forecasts;

(ii) Create data-driven models that emulate the physical environment;

(iii) Set up episodes are combining historical data and forecasts.

[1] https://www.codeproject.com/tips/528243/ssis-fuzzy-lookup-for-cleaning-dirty-data

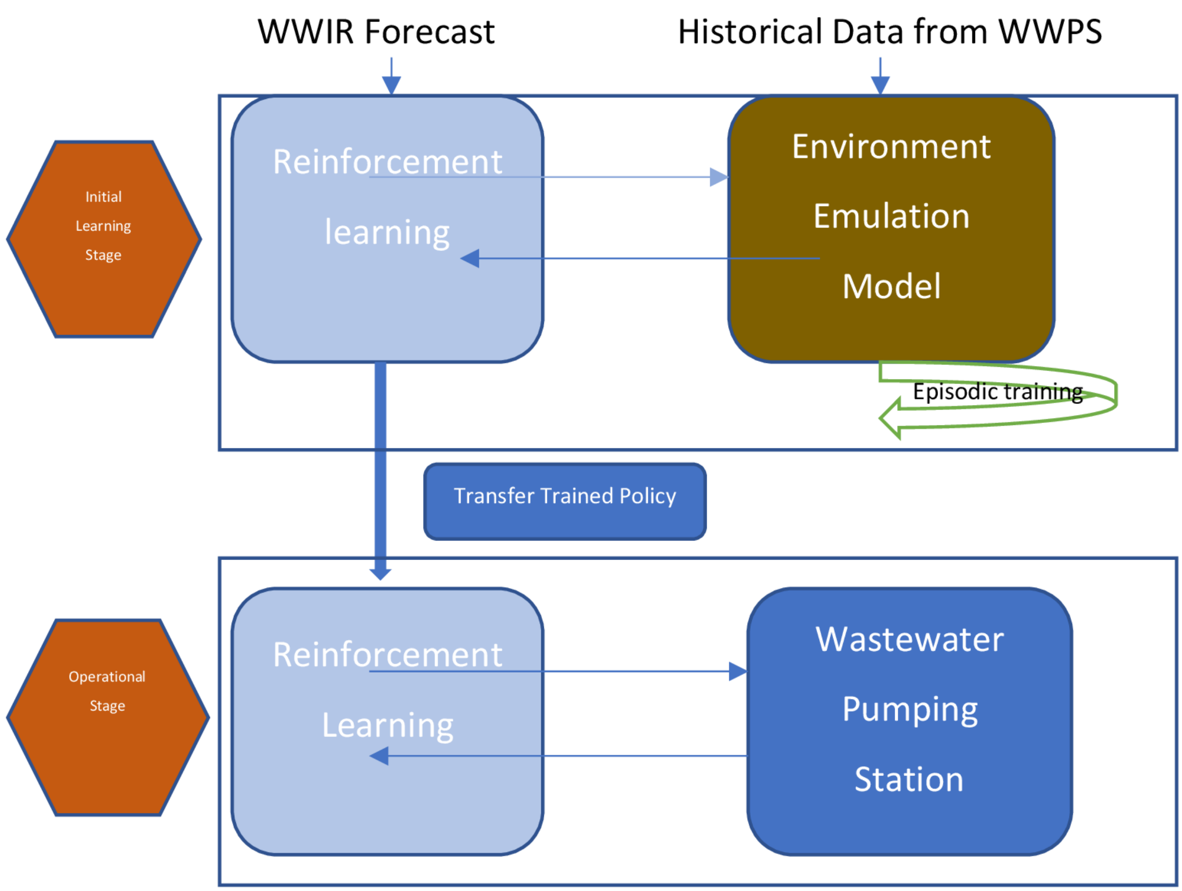


Initial Learning Stage Data-driven method with SCADA

A state vector is constructed from the environment using data such as reservoir level, Wastewater Intake Rate (WWIR) forecasts, pumps online, and current operational set-point, acquired by a set of sensors (IoT) placed with SCADA and subsequently fed to the predictive control strategy. With this information, the algorithm selects actions and power set-point for each pump unit.

Operational stage

The trained data is transferred to an operational setup and applied to the physical wastewater pumping station. ML learning falls under supervised, unsupervised, and reinforcement. We intend to use Reinforcement Learning (RL) at this stage, which is one of three basic machine learning paradigms. Reinforcement learning (RL) is a field of machine learning involved with how software drivers take up measures in an environment to maximize some notion of collective reward and minimizing its penalty. We apply data-mining algorithms to create models from data and generate synthetic data for pre-training the RL algorithm, without the need to interact with the system physically. Reinforcement learning differs from other machine learning methodologies in that the algorithm is not instructed on how to execute a task but works through the challenge on its own. Probabilistic forecasts generated through the learning of the WWIR are used as one of the inputs of the RL control algorithm, to provide the control strategy for uncertainty.



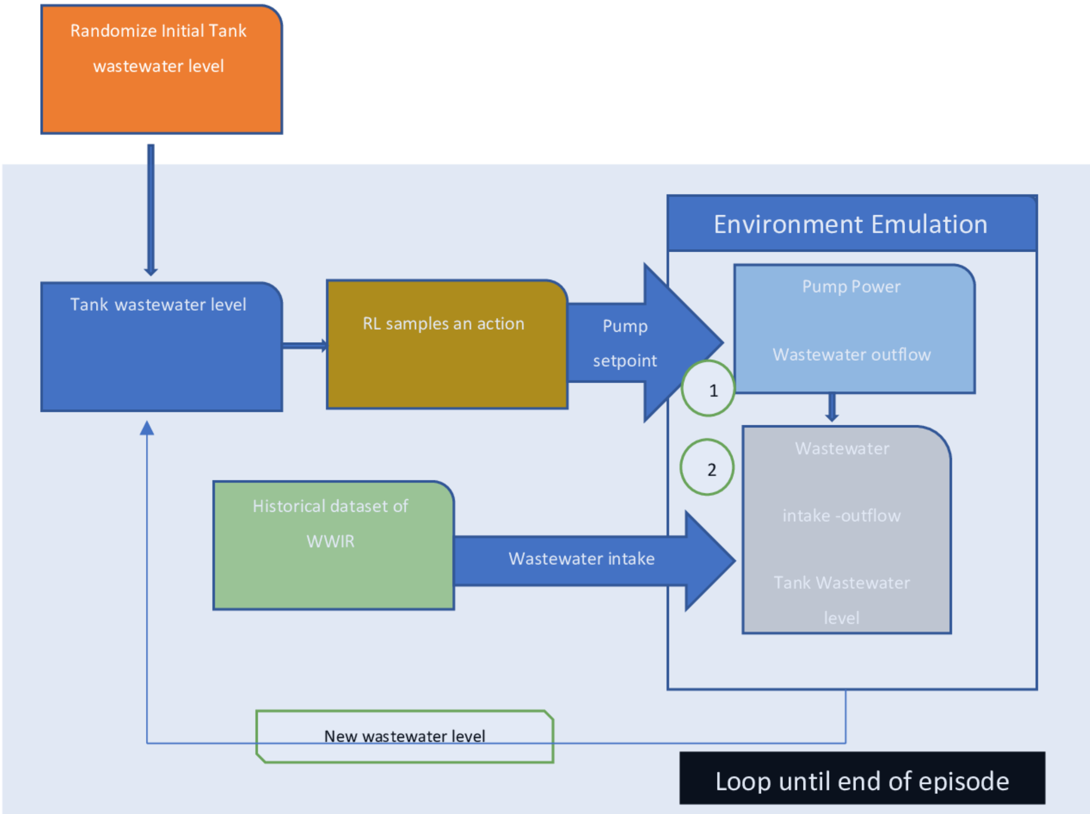
The main distinction between Reinforcement Learning (RL)and Supervised Learning (SL) is;

SL is the process of learning from a training set and then applying that learning to a new data set. Supervised Learning uses the existing available data and makes use of that data to predict patterns. RL is the process of dynamically learning by adjusting actions based on continuous feedback to maximize a reward. “Reinforcement learning can learn from its experience through trial and error.”[2]

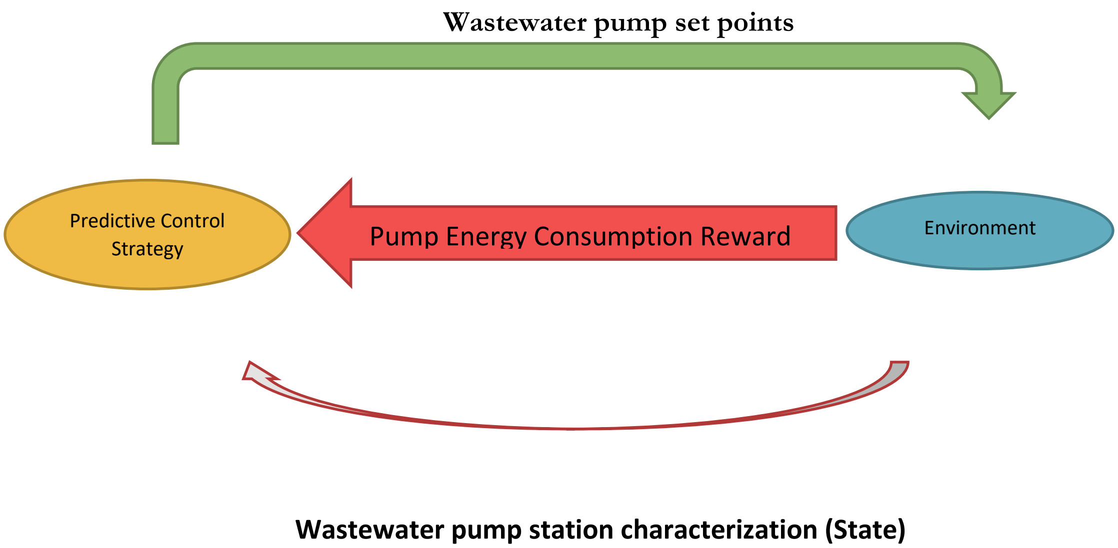
The main objective is to propose and implement predictive pump control policies that optimize energy consumption. The pumps’ energy consumption reflects the reward that provides feedback and allows the algorithm to learn on an ongoing basis

Episodic Training

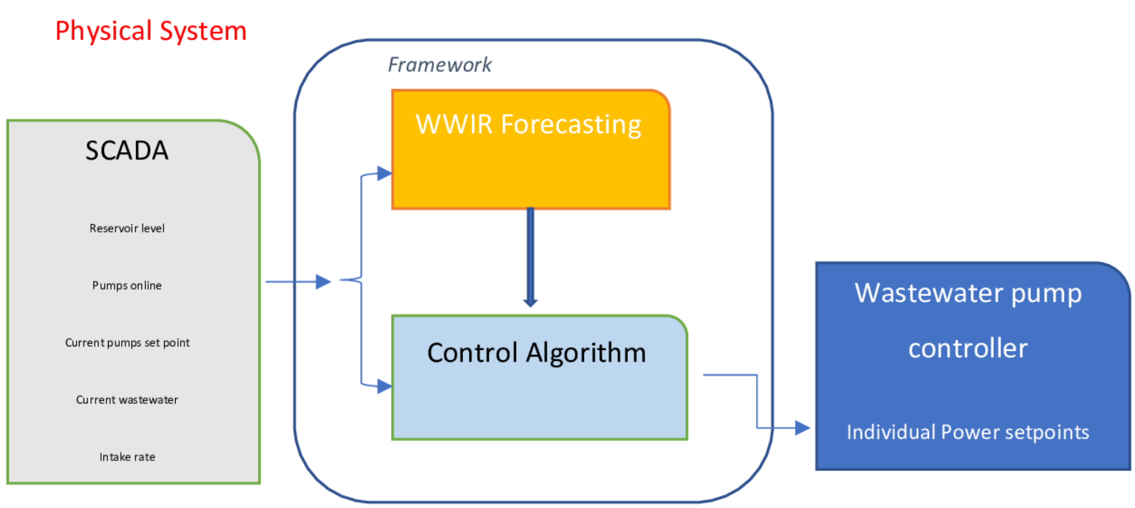
[2] https://pythonistaplanet.com/pros-and-cons-of-reinforcement-learning/



At the beginning of the episode, the initial level of the wastewater tank is randomly initialized. In contrast, for the remainder of the steps of the episode, the wastewater level is a direct effect of the pump operation, i.e., higher pumping power results in a lower level, while decreasing the pumping operation leads to an increase in the tank level. The pumping operation (i.e., power set-points) is characterized by the RL control policy, characterized by a neural network that utilizes the state vector as the network input. The selected action is used to the emulated environment: the first model translates pumping power into a wastewater outflow rate. In contrast, the second one combines the wastewater outflow rate with the WWIR to simulate the shift in the tank level. This revised value is then used at the start of the next step, and the cycle is repeated



After the initial learning stage, during the optimization of the control policy before integration with the real system, some iterations with the real environment may be required to adjust the policy due to contradictions between the emulated and real system



Combined schematic diagram

1. Collect the state characterization from the SCADA

2. Generate the WWIR probabilistic forecasts

3. Sample an action from the control policy

4. Apply the action to the physical environment.

5. Observe the state transition

6. Measure the power consumption (reward)

7.Store the vector [state, action, reward, new state]

8. Update the control policy