D3.3 FIWARE-enabled applications for wastewater treatment

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Executive Summary

The Amsterdam West Wastewater Treatment Plant (Amsterdam West WWTP), owned by Waternet, has a capacity of 1 million population equivalent that serves the city of Amsterdam and consists of 7 treatment lanes. The climate footprint of the WWTP is by a substantial part negatively impacted by greenhouse gas (GHG) emissions and energy consumption for aeration. However, the current operational control of the WWTP is locally distributed and the existing control loops are not tuned for reducing climate impact effects. Hence, to enable more effective plant-wide control, **the aim of this demo case is formulated as improving the use of near real-time plant data and external data sources to minimise the climate footprint of the WWTP, while meeting effluent quality criteria**. This report describes the methods, algorithms and concepts which are applied in the development of a collection of smart applications. To this aim, one of the treatment lanes of Amsterdam West WWTP has been converted into a research lane where various sensors have been deployed. The resulting extensive sensor data set allowed further analysis and enabled the development and training of data-driven models which served as core components of the smart applications.

The WWTP smart application suite consists of (i) an automatic data validation and reconciliation (DVR) framework where crucial sensor data (ammonium and nitrate) is checked for errors and anomalous data values are reconciled by model predictions, (ii) monitoring ('soft sensor') algorithms which estimate the influent flow per treatment lane and (current) air flow to the aeration tanks, allowing the calculation of load and energy consumption respectively, (iii) a data-driven model, also referred to as the digital twin of the WWTP, that estimates nitrous oxide (N_2O) gas emissions and other key process variables and (iv) an AI-based control agent that minimises N_2O emissions and energy consumption, while complying with the effluent quality requirements. Finally, output of the data validation, soft sensor and control agent is sent to dashboards to inform the user of the operational state of the WWTP research lane. For all applications, algorithms from the field of AI have been applied, trained and tested. To this aim, sensor data have been collected, examined and prepared for further training and selection of the data-driven AI models. Models have been selected using test data sets using performance indicators for prediction accuracy and preventing under- or over-parametrization.

Development, training and selection of the models led to the following, specific conclusions and perspectives for each application case:

i. The autoencoder neural network models of the DVR proved to be highly accurate for forecasting NO_3 and NH_4 when forecasting with a window from 5 minutes to about 2 hours. There is room for improvement for longer prediction horizons, e.g. by training and deploying another autoencoder model with a time resolution of 1 hour or more. Overall, the DVR promises to provide a robust and accurate screening and correction layer for further use of sensor data in the digital twin and control agent – especially for anomaly events with a short duration. The DVR procedure can be easily extended to other sensor signals;
ii. The soft sensor for the influent volumetric flow is a recurrent neural network that is able to accurately forecast the influent flow per treatment lane with a horizon of 75 minutes, which is key for using these data for smart control purposes. The soft sensor is fed by the total influent volumetric flow, rainfall data and a rule-based model estimate of the flow per lane. Furthermore, the soft sensor for estimating the air flow is important for the estimation of energy consumption per treatment lane, and therefore a crucial input for smart control. and has been successfully trained on valve settings, pressure and energy consumption of the blowers.

iii. The digital twin model predicts process variables which are relevant for getting insights in the WWT process, and serves as a basis for the smart control agent. The idea of feeding the digital twin with validated sensor signals as well as unmeasured key process variables (e.g. air flow) is a proof of concept which is very suitable for other (water) industrial processes due to its high performance in accuracy. Furthermore, the outputs of the digital twin have multiple advantages: (i) increased process insight, (ii) (more accurate) insight into key performance indicators (e.g. energy, climate impact), (iii) means of decision support in case the digital twin is used to simulate process behaviour e.g. when shutting of the blowers for maintenance, (iv) serves as a virtual copy of the plant such that optimal control policies can be calculated on the fly.

iv. The control agent is trained using the outputs of the digital twin model and the influent soft sensor, and different training data sets were selected to allow evaluation of different responses to weather conditions. A deep reinforcement learning (DRL) approach has been followed and two algorithms are used to solve two similar formulations of the optimisation problem. In addition, two reward functions have been formalized to represent the objective for minimising climate impact and penalising the exceedance of NO_3 and NH_4 concentration thresholds of which one reward function penalises high NO_3/NH_4 concentrations more than the other. Moreover, the agents' learned control policies are benchmarked against three control scenarios: i) a baseline, conventional WWTP control where setpoints are fixed by operators, ii) random control policies and iii) classical optimization run offline on the different setups. Reward function evaluations show that the RL learnt policies approach the function evaluations of 'classical', off-line optimization runs, hence indicating a promising outcome in case the DRL control agent will be deployed. As a recommendation and as a first step in deployment, carefully running the control agent for short periods of time should be considered to get data sets which allow fine-tuning of the control model to improve the controller's performance.

In summary, this demo case (i) showcases the excellent performance of using AI models in the water sector, and proves that AI can substantially contribute to the intelligent control of a WWTP, (ii) gives insights in the reduction of nitrous oxide emissions and the influence of control actions based on the outcome of the DVR, digital twin and soft sensors, as well as the experimentation with control policies and evaluation of results and (iii) contributes to reducing climate impact. Specifically, it is estimated that half of the climate footprint of Waternet is linked to nitrous oxide emissions from WWTPs.

As such, the demo case Amsterdam West WWTP directly contributes to the acceleration of the dual – green and digital – transition, which is seen as a necessity in order to reach the climate goals by 2030. Ultimately, the outcome of this task and work package will assist in bridging science to practice and science to policy across Europe. The EU added value (EAV) is detailed in Section VII.

Related Deliverables

D1.1 Requirements from Demo Cases

D4.4 FIWARE4_Intelligent Control for Wastewater Treatment

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List of Acronyms/Glossary

AI	Artificial Intelligence
AT	Aeration tank
ASP	Activated Sludge Process
CRISP-DM	Cross Industry Standard Process for Data Mining
DNN	Deep Neural Network
DNT	Denitrification (tank)
DRL	Deep Reinforcement Learning
DS	Dry solids
DT	Digital Twin
DQN	Deep Q Learning algorithm
EAV	European added value
F4W	Fiware4Water project
FCT	Facultative (tank)
GHG	Greenhouse Gas
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Errors
ML	Machine Learning
N_2O	Nitrous Oxide
NaN	Not a Number
NH_4	Ammonia
NO_3	Nitrate
NGI	Next Generation Internet
NIT	Nitrification (tank)
R^2	Coefficient of Determination
RAS	Return Activated Sludge
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RL	Reinforcement Learning

SAC	Soft Actor Critic algorithm
WWT	Wastewater Treatment
WWTP	Wastewater Treatment Plant