EGDC Case study – SAWACO – The AI Digital Platform for SWRO

March 2026

EUROPEAN GREEN DIGITAL COALITION

Funded by the European Union

1 Introduction

The European Green Digital Coalition (EGDC) is an initiative of companies, supported by the European Commission and the European Parliament, based on the request of the EU Council, which aims to harness the enabling emission-reducing potential of digital solutions on all other sectors.

The main aim of the EGDC is to maximise the sustainability benefits of digitalisation within the ICT sector, while supporting sustainability goals of other key sectors such as energy, transport, agriculture, and construction. The Coalition recognises the need for science-based methods to estimate the reduction and avoidance of greenhouse gas (GHG) emissions by specific ICT solutions across sectors. This will accelerate the sustainability and circular transitions of these sectors while contributing to an innovative, inclusive, and resilient society.

To support the EGDC, a set of case study calculators are developed to provide a practical example of calculating the net carbon impact of a green digital solution in line with the European Green Digital Coalition (EGDC) methodology. This work aims to support the members of the EGDC with Action 2 of the EGDC Declaration.

This case study methodology accompanies the '*AI Digital Platform for SWRO Desalination* (SAWACO)' case study calculator and provides further details, additional context and transparency around the case study calculator to ensure the outcomes of the case study are interpreted and used correctly.

Funded by
the European Union

Disclaimer for European Parliament Pilot Project – European Green Digital Coalition (EGDC) Case Studies

The following disclaimer is intended to provide clarity and context for the case studies prepared as part of the EP Pilot Project, which have showcased the net carbon impact of specific digital solutions using the EGDC ICT Methodology developed during the project:

1. Purpose of the Case Studies:
The case studies served multiple purposes, including:

- **Development of the Methodology:** They contributed to the development of the EGDC ICT Methodology. These case studies were conducted concurrently with the methodology's creation and served as a valuable testing ground for its initial formulation.
- **Application Examples:** They provided practical examples of how the methodology can be applied to real-life use cases. These case studies were essential in demonstrating the practicality and effectiveness of the methodology when applied to concrete situations.
- **Identification of Improvement Areas:** By conducting these case studies, we aimed to highlight parts of the calculation in need of improvement. They shed light on the challenges and limitations inherent in using available data and indicated the necessary steps to move towards best practices in assessing net carbon impacts.

2. Data Quality as a Key Determinant:
It is imperative to emphasize that data quality is a fundamental determinant of the quality and reliability of the case studies. The accuracy and completeness of the data used significantly influence the outcomes and findings of these case studies.
It is essential to acknowledge that the data available for each case study may differ in terms of accuracy, granularity, and coverage. As a result, the case studies may not necessarily represent the best practice application of the EGDC ICT Methodology. Instead, they reflect the application of the methodology at various stages of data availability.

3. Liability for Errors/Omissions:

While reasonable steps have been taken to ensure that the information contained within the case studies is correct, the EGDC gives no warranty and makes no representation as to its accuracy. We accept no liability for any errors or omissions that may be present in the case studies, methodology, or related information. Users and readers are advised to exercise their judgment and seek further clarification if needed, as the information provided may evolve over time and depend on external factors beyond our control.

4. Appropriate Use of the Case Study Calculators:
The case study calculators are intended for educational and informational purposes. They rely on certain assumptions and input data to generate results.
The results of the calculators are specific to the implementation of the ICT solution and may not be representative for other implementation contexts.
As such, it is imperative for users to refrain from directly extrapolating these results to ICT solutions or implementation contexts that may seem conceptually similar.
Instead, users are advised to use the calculators as a means to understand the practical application of the EGDC ICT Methodology, thereby equipping themselves with the knowledge required to develop customized calculators specifically tailored to their unique ICT solutions and implementation circumstances.

In conclusion, these case studies provide valuable insights into the calculation of the net carbon impact of digital solutions through the practical application of the EGDC ICT Methodology. However, it is vital to exercise caution when interpreting the results, considering the variances in data quality and the evolving nature of the methodology. The findings are indicative of the methodology's potential and its room for refinement as we work towards more accurate and comprehensive assessments of net carbon impacts.

2 Results

Website: https://www.sawaco.com

Email: awadi@sawaco.com

ICT Solution and assessment overview	Organisational contribution
This case study assesses an AI-powered digital optimisation tool used at SAWACO's CFRO + BWRO seawater desalination unit in Jeddah, Saudi Arabia. The solution analyses operational data and recommends new setpoints (e.g., pump pressure, brine flow, recirculation rates) to reduce electricity consumption while maintaining stable plant performance. In the reference scenario, the plant is operated using manual monitoring, operator experience and fixed operational settings. While functional, this limits energy efficiency and can increase operating costs and the carbon footprint. This case study is an ex-post assessment for the year 2024. Baseline and solution electricity consumption are annualised using measured plant data (data period start: 01-Jan-2024; data period end: 20-Nov-2024), with results expressed per cubic metre of potable water produced.	SAWACO partnered with a technology provider to co-design, validate, and deploy the AI Digital Platform for SWRO optimisation at SAWACO's CFRO + BWRO desalination unit in Jeddah. SAWACO contributed the operational context and plant data required to develop and train the model, facilitated integration with the existing SCADA environment, and supported commissioning by testing and adopting the AI-recommended operating setpoints within day-to-day operations. This aligns with A-level classification as defined by ITU-T L.1480 (contribution of implementing the integrated solution or the innovation of the solution).
Quantified impacts	**Other identified impacts**
	Reduced electricity consumption at the desalination unit directly lowers operational energy demand (kWh) and, for a given grid emission factor, reduces associated indirect (Scope 2) GHG emissions from electricity generation. Operationally, improved control of key setpoints can increase process efficiency by maintaining closer-to-optimal pressures, flows, and recovery conditions,

<table>
<tr><td>Assessment period:</td><td>2024 (annualised from measured plant data)</td><td rowspan="4">reducing unnecessary pumping and smoothing performance variability.

More stable operation may also reduce mechanical and hydraulic stress on equipment (e.g., high-pressure pumps, energy recovery devices, and membranes) by avoiding inefficient or off-design conditions, which could in turn contribute to improved reliability and potentially longer component lifetimes (e.g., reduced premature membrane fouling/damage and/or less frequent replacements), although these effects are not quantified in this case study.

Reduced electricity use also leads to operating cost savings for the plant operator through lower purchased electricity.</td></tr>
<tr><td>Net carbon impact range:</td><td>-141.6 to -175.4 tCO2e/year</td></tr>
<tr><td>Net carbon impact:</td><td>-157.6 tCO2e/year</td></tr>
<tr><td>Net impact per m³ of potable water:</td><td>-0.2585 kgCO2e/m³/year</td></tr>
</table>

3 Methodology

Name of solution: SAWACO - The AI Digital Platform for SWRO	
Assessment Objective	The purpose of this assessment is to quantify the net avoided carbon emissions enabled by an AI-based operational optimisation tool deployed at SAWACO's CFRO + BWRO seawater desalination unit in Jeddah, Saudi Arabia. The assessment compares electricity consumption before and after implementation of the AI-recommended operating setpoints, using measured plant data annualised for the assessment period (2024). The results are reported per cubic metre of potable water produced and include first-order solution emissions associated with AI model training.
Solution Description	Seawater reverse osmosis (SWRO) desalination is electricity-intensive because it relies on high-pressure pumping. Under normal operations, plants rely on manual monitoring, operator

	experience, and fixed operational settings, which can limit energy efficiency. The AI Digital Platform for SWRO is a cloud-based software tool that connects to the plant's existing SCADA system to monitor, store and analyse operational data from key instruments. The AI acts as a digital assistant for operators, detecting patterns in live and historical data to predict system behaviour and recommend operating setpoints that reduce electricity use while maintaining stable plant performance. For SAWACO's CFRO + BWRO unit, the model was trained on historical operational data and used predictive analytics and optimisation algorithms to recommend adjustments to controllable parameters (e.g., pump pressure, brine flow, recirculation rates). Implementing these recommendations reduced the specific energy consumption (kWh per m^3 of water produced) without physical equipment changes. The avoided emissions mechanism is achieved through reduced grid electricity consumption per unit of water produced, which lowers associated emissions from electricity generation.

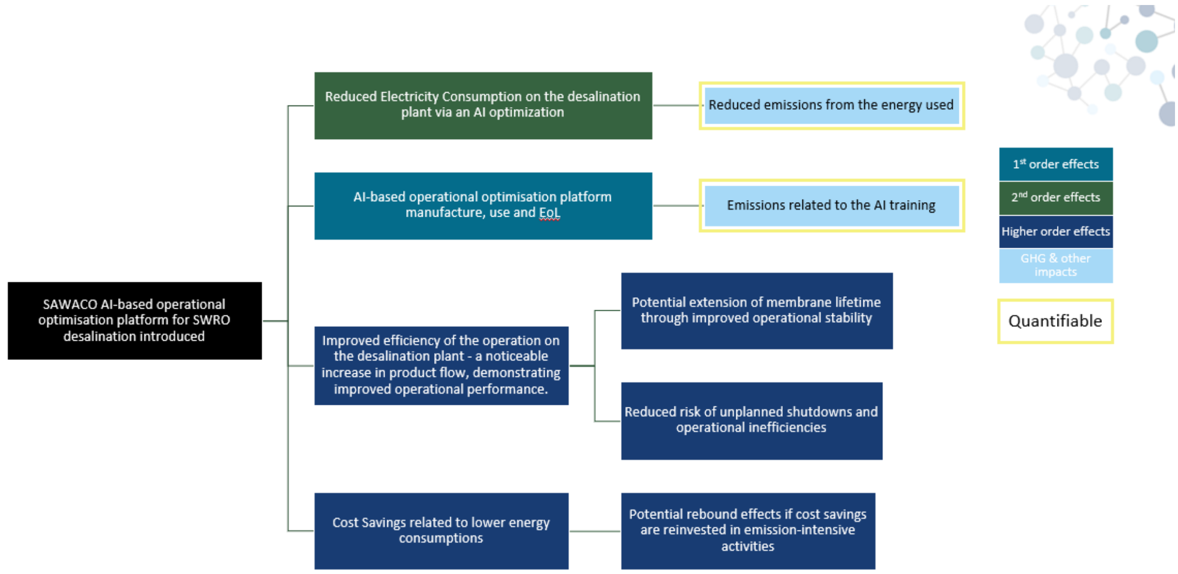
Solution Boundary	The solution boundary covers the digital elements required to develop and implement the AI-based optimisation and the desalination operational context in which setpoint recommendations are applied. **Digital components (included where data is available):** • AI model development and training on a standard computer (72 hours), including electricity use and an allocated share of the device lifecycle footprint. • SCADA-connected data monitoring and analytics capability used to derive operating recommendations (modelled in this case study via the AI training activity). **Operational system (context for 2nd order effects):** • CFRO + BWRO desalination unit (pumping and associated electricity consumption). No dedicated additional hardware was installed or operated continuously for this solution; therefore, first-order effects are limited to the short AI model training activity as per the data provided.
Components of the solution: 1) Computer used for the AI training	
Functional Unit	kgCO2e per m³ of potable water produced per year
Calculation Boundary	The calculation represents an annualised assessment for the year 2024. Electricity consumption in reference and solution scenarios is based on measured plant data and annualised to a one-year period for comparability (data period start: 01-Jan-2024; data period end: 20-Nov-2024). The geographic boundary of the solution is limited to Jeddah, Saudi Arabia, and the grid electricity emission factor applied corresponds

	to Saudi Arabia (0.55 kgCO2e/kWh, as per the calculator emission factor table).
Reference scenario	In the reference scenario, the desalination unit is operated without AI-based optimisation, relying on manual monitoring, operator experience, and fixed operational settings. Electricity consumption is measured as specific energy consumption (kWh/m³) and total electricity use is annualised. For comparability with the solution scenario water production volume, the baseline electricity consumption is adjusted to correspond to the volume of potable water produced in the solution scenario. This is done by multiplying the baseline specific energy consumption by the solution scenario water production volume and then annualising based on the measured data period.

Description of 1st order effects	The first-order effects of the SAWACO solution are the direct emissions associated with developing the AI optimisation (model training). Based on the data available for this case study, no dedicated additional hardware was installed or operated continuously; therefore, first-order effects are limited to the short AI training activity on a standard computer. Included first-order elements: • Electricity consumption during AI training (6.48 kWh over 72 hours) multiplied by the Saudi Arabia grid emission factor. • Allocated lifecycle emissions for the computer used during training (proxy value of 0.31 kgCO2e over the 72-hour training period). Other potential digital infrastructure impacts (e.g., cloud computing beyond the training activity) were assessed as immaterial for the short training duration and are not included.

Description of 2nd order effects	Using a consequence tree, the 2nd order effects are the direct operational consequences of deploying the AI optimisation tool in the desalination unit. Primary change (intervention): AI-recommended setpoints are implemented in day-to-day operations. Direct consequence chain: • Optimised operating setpoints reduce specific energy consumption (kWh per m^3 of potable water produced). • Lower electricity consumption reduces grid-related GHG emissions for the same functional unit. Quantification approach: • Avoided emissions are calculated as the difference between annualised baseline electricity emissions and annualised solution electricity emissions, using the Saudi Arabia grid emission factor. • In this case study, the annualised reduction in electricity use is 286,482 kWh/year (6.47%), corresponding to 157,565 kgCO2e/year of avoided emissions and a net result of -157.6 tCO2e/year after first-order effects. Scope note: • The 2nd order effect is limited to operational electricity-related emissions at the desalination unit. Upstream/downstream impacts (e.g., changes in chemicals use, maintenance, or water distribution) are treated as potential higher order effects unless quantified.
Description of higher order effects	Potential higher order effects identified for this solution include: • Reduced material consumption and waste: the AI platform may help protect equipment (e.g., membranes and pumps) by detecting performance issues earlier and recommending operating setpoints that reduce stress on the system. This may extend membrane lifetime and/or

	reduce membrane replacement frequency by helping prevent early fouling or damage. • Changes in chemicals use and maintenance: earlier detection of membrane fouling risk could enable better-timed cleaning (CIP) or other maintenance interventions. Depending on operational practices, this could increase or decrease cleaning frequency and associated chemical use, with corresponding upstream emissions impacts. • Improved operational stability and output: improved control and more stable operations (e.g., fewer unplanned shutdowns, more stable water production) could indirectly affect resource use and operational efficiency beyond electricity (e.g., reduced waste, fewer off-spec events). • Rebound effects from cost savings (e.g., reinvestment of savings into activities that may increase emissions) may occur depending on organisational decisions. These effects were not quantified in this case study due to data limitations and are provided for interpretation context only.
Mapping of 2nd order and higher order effects	



Assessing the impact of higher order effects

Potential rebound (higher order) effects from electricity cost savings were considered on a quantitative basis, since reduced electricity expenditure could—in principle—be reallocated to other activities with higher carbon intensity. However, given the very low electricity price in Saudi Arabia (0.053 USD/kWh), the associated cost savings are small, and the resulting rebound impact is deemed negligible relative to the emissions savings from reduced electricity consumption.

Description of calculation	**1st Order Effects** First-order effects represent the emissions associated with developing the AI optimisation model (model training). Based on SAWACO-provided information, model development and testing were carried out on a standard computer for approximately 72 hours. First-order emissions include: (i) electricity consumption during AI training multiplied by the Saudi Arabia grid emission factor; and (ii) an allocated proxy share of the computer lifecycle footprint over the training duration. **2nd Order Effects** Second-order effects represent the avoided emissions from reduced grid electricity consumption at the desalination unit after implementation of AI-recommended operating setpoints. Avoided emissions are calculated as the difference between annualised baseline electricity emissions and annualised solution electricity emissions, using the Saudi Arabia grid emission factor (0.55 kgCO2e/kWh, as per the calculator). **Net Carbon Impact** Net carbon impact is calculated as avoided emissions (2nd order effects) minus first-order emissions associated with AI model training. Results are reported per cubic metre of potable water produced and annualised for the assessment period.
Net Carbon Saving Impact of the Solution	**Desalination unit – annual impact** **1st order effect (emissions from solution activity):** • 0.005 tCO2e/year (5.20 kgCO2e/year) **2nd order effect (avoided emissions from reduced electricity use):** • -157.6 tCO2e/year **Total net carbon saving impact:** • -157.6 tCO2e/year **Other metrics:**

	% energy savings through use of the solution: • 6.47% **Net impact per m³ of potable water:** • -0.2585 kgCO2e/m³/year
Uncertainty and sensitivity analysis	**Total carbon savings enabled (tCO_2e/year):** Calculated Net Avoided Emissions: -157.6 Lower uncertainty range: -141.6 Higher uncertainty range: -175.4 **Uncertainty analysis:** Electricity consumption and the grid electricity emission factor are the main drivers of uncertainty because they determine the magnitude of avoided emissions. In contrast, first-order effects associated with AI model training are immaterial relative to operational electricity savings.
Assumptions	**Emission Factors** • It is assumed that the electricity grid emission factor used for Saudi Arabia accounts for full lifecycle emissions (including upstream fuel supply, generation, transmission and distribution). **Solution hardware and IT boundary** • SAWACO confirmed that no dedicated additional hardware was installed or operated continuously for the purpose of this solution. • First-order effects are therefore limited to AI model training on a standard computer over ~72 hours, plus an allocated share of the computer lifecycle footprint using a conservative laptop proxy.

	Baseline adjustment and comparability • Baseline electricity consumption is adjusted to match the solution scenario water production volume by applying baseline specific energy consumption (kWh/m³) to the solution water volume. • Electricity and water data are annualised for comparability across the assessment period. **Operational context** • Feedwater conditions (temperature, conductivity, SDI) are not direct calculation inputs but can influence desalination-related energy use; results should be interpreted in the context of the recorded average conditions for the assessment period. It is assumed that the reference and solution scenarios are broadly comparable regarding feedwater conditions and maintenance practices (e.g., membrane cleaning intervals).
Data sources	**Data provided by SAWACO / project partners:** • EGDC Case Study SAWACO.xlsx (calculator inputs, calculations, results, assumptions and emission factors). • Data request - SAWACO Desalination - NEC Response query log 19012025 (as referenced within the calculator). **Additional reference:** • Case Study Call - SAWACO.pptx (solution description and avoided emissions mechanisms discussed during the case study call). **Secondary data sources:** Emission factors and proxy data sources are referenced within the calculator, including the Saudi Arabia grid emission factor table and Apple product environmental reports for the laptop proxy.
Input adjustments and key considerations for usage of results	**List of things to consider if using results in other use cases:**

	• Country/region (electricity grid emission factor). • Plant type and configuration (e.g., SWRO, BWRO, recovery rates, pump configuration). • Baseline specific energy consumption (kWh/m³) and baseline operating practices. • Feedwater conditions (temperature, conductivity, SDI) and pretreatment requirements. • Water production volume and baseline electricity is normalised to the functional unit. Data period coverage and representativeness (seasonality and maintenance of events such as membrane cleaning).
'Do no significant harm' criteria	Do not foresee any negative impacts on any of the EU Taxonomy's environmental nor social objectives and strongly supports objective 1. The solution supports climate change mitigation by reducing grid electricity consumption per unit of potable water produced. Potential wider considerations include ensuring responsible data handling within SCADA-connected systems, and that any operational changes do not negatively affect water quality compliance or increase chemical consumption; these aspects were not quantified in this assessment.
Key areas for improvement	1. Collect and include a longer continuous measurement period for both the reference and solution scenarios, ideally covering full-year seasonality and capturing key operational events (e.g., membrane cleaning). 2. Primary data for 1st order effects calculations (use of computer) could be used and be specific for the actual model used for the AI training, however, because of the low impact on the solution, it is not considered to be a priority from the materiality perspective.