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### **Digitalization As basic Driver for servitization in Industry and Basic Services” (DADIBAS)**

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## 1 INTRODUCTION

|                          |  |                              |                   |
|--------------------------|--|------------------------------|-------------------|
| <b>Project Title:</b>    | <i>"Digitalization As basic Driver for servitization in Industry and Basic Services" (DADIBAS)</i>   |                              |                   |
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## 2 CONTEXT

The focus of this WP aims to enhance technological processes significantly impacted by asset status and human decision-making, where existing knowledge can be extended. The project focuses on leveraging digitalization in innovative ways to facilitate the non-invasive dissemination of agreed-upon information. This information serves as an anchor for more robust and integrated, process-oriented servitization approaches using Distributed Ledger Technology (DLT). To achieve this, it is crucial to carefully select the most suitable processes for improvement.

The list of relevant tasks is,

T2.1.- Setup of the use case.

T2.2.- Advanced Quality Workflow.

T2.3.- Microservice environment for project usage.

T2.4.- DeepLearning, Transfer Learning and Contrastive Learning tools.

T2.5.- Quantum technology for process assessment.

T2.6.- Decision Transformers in Scheduling Optimization.

T2.7.- Dissemination.

T2.8.- Reporting and Configuration management.

The foreseen deliverables are:

D2.1 .- Use case description: Challenges & technological requirements [M9]

D2.2 .- Digital models and process improvement [M42]

D2.3 .- Dissemination report and KPIs [M48]

The focus of this document is to address the first deliverable (D2.1). It took longer than initially foreseen, since negotiation with different agents, as well as discussions to find a suitable environment extended over several months.

However, we strongly believe that servitization can be extended further in many different sectors (including industry but also other business services such as finance, health, or education) from the technical point of view but also from the involved asset management perspective, which demands the integration of operations and maintenance policies. Therefore, a relevant research question to be addressed is, **how to articulate transparency on data from assets, performance, and degradation models to foster an increased servitization level at process or service levels?**

There are numerous areas of application and a wide variety of problems to address, each with its own unique challenges and requirements. Similarly, there are many different types of algorithms that can be applied, providing a broad range of potential solutions. This diversity makes it possible to identify a significant number of use cases. In this context, the focus of this

document is to narrow down the scope to one specific application: water management in reservoirs. The goal is to optimize revenue from water turbine operations while ensuring that reservoir levels remain sufficient to meet water demands. By addressing this use case, the document seeks to explore practical ways to balance economic benefits with sustainable water management, leveraging advanced algorithms to achieve this delicate equilibrium.

### **3 USE CASE DESCRIPTION: OPTIMIZATION OF HYDROPOWER SYSTEMS**

The optimization of hydropower systems plays a crucial role in maximizing economic benefits while effectively managing water as a scarce resource. A typical hydropower system includes reservoirs that store water, releasing it for energy generation at the most advantageous times. The amount of water released is constrained by factors such as the reservoir's volume and the capacity of the channel. If a reservoir contains insufficient water, energy cannot be generated; conversely, if water is abundant and its use is unrestricted, optimization becomes irrelevant.

The challenge of hydropower system management lies in determining the optimal water flow from each dam over specific time periods. Known as Hydropower Reservoirs Operation Optimization (HROO) in the literature, this problem can pursue different objectives, such as maximizing energy output, minimizing the gap between energy supply and demand, or maximizing revenue from energy generation. Revenue optimization requires storing water during low-price periods and releasing it during peak-price periods when energy commands higher prices. However, this approach is complicated by the interdependencies of multiple reservoirs in a system, where water released from one reservoir flows into another, necessitating holistic planning. Additionally, the electricity market's fluctuating energy prices, including peak and off-peak periods, introduce further complexity to the decision-making process.

This use case was not in the literature and addresses it by introducing the Hydropower Reservoirs Intraday Economic Optimization (HRIEO) problem, focusing on short-term management with an emphasis on maximizing economic benefits. Unlike traditional approaches that optimize over longer timeframes (days, months, or years), the HRIEO problem incorporates finer time intervals (hours or minutes). This allows the model to capture critical factors such as hourly price fluctuations, water delay between release and generation, and various operational constraints. Examples of such constraints include the costs of starting power groups, turbine efficiency restrictions, channel gate limitations, and water hammer effects. Additionally, the European Regulation (2017/2195), which mandates price matching in electricity markets every 15 minutes, highlights the need for models that integrate finer time discretization to meet regulatory requirements and adapt to changing market dynamics.

The proposed HRIEO model aims to provide a more accurate and practical approach for managing hydropower systems in real-time. It incorporates two complementary solution methods: (1) an exact approach using Mixed-Integer Linear Programming (MILP) solved with a branch-and-bound algorithm and (2) an approximate method using a Particle Swarm Optimization (PSO) algorithm.

By integrating fine-grained time discretization, market price fluctuations, and operational constraints, this work offers valuable insights and tools for improving the short-term management of hydropower systems, ultimately contributing to enhanced economic performance and sustainable energy practices.

## 4 LITERATURE REVIEW RELATED TO THE USE CASE

The literature review related this use case examines existing methodologies for optimizing hydropower reservoir operations, highlighting the complexities introduced by intraday market dynamics and the need for fine-grained temporal modelling.

**Hydropower Reservoirs Operation Optimization (HROO).** Traditional approaches to HROO have primarily focused on long-term planning horizons, often spanning months or years. These methods typically employ coarse temporal resolutions, which, while suitable for strategic planning, fail to capture the nuances of intraday market fluctuations and operational constraints. Common techniques in this domain include deterministic optimization models that do not adequately address the stochastic nature of energy prices and inflows.

**Intraday Market Considerations.** With the liberalization of electricity markets and the increasing penetration of renewable energy sources, there has been a significant shift towards short-term markets, including intraday and real-time markets. These markets are characterized by high volatility and rapid price changes, necessitating optimization models that can operate on an hourly or sub-hourly basis. However, the literature reveals a gap in models that effectively integrate intraday market dynamics with hydropower reservoir management, particularly in terms of maximizing economic returns within these short time frames.

**Modelling Approaches.** The review identifies two primary modelling approaches employed in hydropower optimization:

1. **Mixed-Integer Linear Programming (MILP):** MILP models are favoured for their precision and ability to handle complex constraints inherent in hydropower systems, such as turbine operating ranges, reservoir storage limits, and environmental regulations. They are particularly effective in scenarios requiring detailed operational decisions. However, the computational intensity of MILP models increases exponentially with the problem size and the granularity of the time discretization, making them less practical for large-scale or real-time applications.
2. **Metaheuristic Algorithms:** Techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been applied to hydropower optimization problems due to their flexibility and ability to find near-optimal solutions within reasonable computational times. These algorithms are adept at navigating large and complex solution spaces but may require extensive parameter tuning and do not guarantee optimality.

**Operational Constraints and Challenges.** The literature underscores several operational challenges that must be addressed in intraday optimization models:

- **Turbine Start-Up Costs:** Frequent start-stop cycles of turbines, driven by intraday market opportunities, can incur significant costs and mechanical wear, necessitating models that balance economic gains against operational expenses.
- **Water Delay Times:** The time lag between water release from upstream reservoirs and its arrival at downstream turbines introduces complexities in coordination, especially under intraday market constraints.
- **Regulatory Compliance:** Adherence to environmental regulations, such as minimum flow requirements and water quality standards, imposes additional constraints that must be integrated into optimization models.

**Research Gap.** Despite advancements in modelling techniques, the review identifies a paucity of studies addressing the Hydropower Reservoirs Intraday Economic Optimization (HRIEO) problem. Existing models often overlook the intricacies of intraday market participation, such as rapid price fluctuations and the need for swift decision-making processes. There is a clear need for models that can operate on fine temporal scales, incorporate stochastic market behaviors, and remain computationally feasible for real-time application.

In conclusion, the literature review highlights the evolution of hydropower optimization models from long-term, deterministic frameworks to the necessity for short-term, stochastic approaches capable of handling the complexities of intraday markets. It sets the stage for developing and applying models like MILP and PSO to effectively address the HRIEO problem, aiming to bridge the identified research gap and enhance the economic performance of hydropower systems in the context of modern electricity markets.

## 5 REQUIREMENTS

The requirements related to this use case can be divided as follows: technical, operational, data and implementation requirements. Each of them will be explained below.

### Technical Requirements

- a) Hydropower System Infrastructure.
  - A network of interconnected reservoirs, dams, channels, and power groups.
  - Properly designed gates capable of regulating water flow and adhering to operational constraints such as water hammer prevention.
  - Accurate sensors to monitor flow, water levels, and turbine status.
- b) Optimization and Simulation Software.
  - Software capable of handling Mixed-Integer Linear Programming (MILP) for exact optimization.
  - Tools or platforms to implement Particle Swarm Optimization (PSO) or similar metaheuristic algorithms.
  - Computational power to handle fine time discretization and solve the HRIEO problem across multiple time intervals (e.g., every 15 minutes).
- c) Mathematical Models.
  - A piecewise linear function to model:
    - Turbined flow and generated power relationships.
    - Volume-dependent constraints on water outflow based on Bernoulli's principle.
  - Incorporation of delay models for cascaded reservoirs.

### Operational Requirements

- a) Regulatory Compliance:
  - Alignment with energy market regulations, such as the European Regulation (2017/2195), requiring price matching in the wholesale market at 15-minute intervals (Commission European, 2017).
- b) Gate Operation Policies:
  - Limits on frequent or abrupt gate operations to prevent water hammer and excessive wear.
  - Scheduling policies to minimize abrupt outflow changes and optimize operational costs.

c) Turbine Management:

- Procedures to minimize startup costs when activating turbines.
- Avoidance of restricted zones of turbine efficiency to maintain system stability.

**Data Requirements**

a) Energy Price Forecasts.

- Accurate predictions of energy prices at fine-grained time intervals (hourly or quarter-hourly) for the entire day.

b) Water Inflow Projections:

- Reliable forecasts of water inflow from rivers or rainfall for all reservoirs in the system.

c) Hydraulic and Energy Production Data:

- Data on reservoir height, flow capacities, and turbine characteristics.
- Historical and real-time data to inform optimization models and validate results.

d) Delay Characteristics:

- Precise measurements of channel lengths and corresponding water travel times to account for delays between outflow and energy generation.

**Implementation Prerequisites**

a) Simulation and Testing:

- Rigorous testing of optimization models on historical or simulated data to ensure their validity and performance.

b) Integration with SCADA Systems:

- Real-time integration with Supervisory Control and Data Acquisition (SCADA) systems for operational monitoring and decision-making.

c) Cross-Disciplinary Expertise:

- Collaboration between hydropower engineers, operations researchers, and market analysts to address technical and economic aspects effectively.

d) Infrastructure Upgrades:

- Potential upgrades to existing hydropower infrastructure to accommodate finer control mechanisms and advanced monitoring.

## 6 METHODOLOGY

The methodology combines an exact approach (MILP) with a metaheuristic (PSO) to address the use case problem from different perspectives, comparing the effectiveness of both methods. Advanced optimization techniques, including improved initialization and parameter tuning, were employed to enhance results and explore improvements in solution quality.

### MILP (Mixed Integer Linear Programming)

The MILP (Mixed Integer Linear Programming) formulation was chosen as the exact method for solving the HRIEO problem, using the branch and bound algorithm (Wolsey, 1998) provided by the Gurobi solver (Gurobi 2020). This approach ensures precision and efficiency in handling the problem's complexity. The model was constructed by defining the necessary sets, parameters,

and variables, allowing for a detailed mathematical representation of the system's components and behaviour.

The objective function was designed to maximize economic profit while accounting for penalties associated with operating within limit zones and power group startups.

Constraints were incorporated to model critical aspects such as reservoir volume balances, inflow and outflow dynamics, and flow variations. Additionally, physical limitations, such as maximum and minimum allowable volumes and flows, were enforced. Penalties for abrupt changes in flow and specific constraints to address water hammer effects were also included to ensure system stability and operational feasibility.

To address non-linear aspects of the problem, convex combinations were used to model piecewise linear functions. These included the relationship between turbined flow and generated power, as well as flow limitations based on reservoir volume. By employing this formulation, the MILP model effectively captured the physical, operational, and economic complexities of the problem, ensuring a robust and accurate solution framework.

### **Particle Swarm Optimization (PSO).**

Particle Swarm Optimization (PSO) was applied to solve the HRIO problem (Kennedy and Eberhart, 1995), where each potential solution was represented as a numerical array encoding the outflows of reservoirs over time. The algorithm iteratively updated the positions and velocities of particles, steering them towards the best local and global solutions. The evaluation function used for assessing each solution was derived from the MILP model equations, ensuring that the two methods could be compared directly.

Several strategies were explored to improve the performance of the PSO algorithm (Bratton and Kennedy, 2007). Different solution encoding methods were tested, including one based on direct outflows and another using variations in outflows between time intervals. Boundary handling techniques, such as "reflection" and "velocity reduction," were used to address particles that moved out of the feasible solution space. Additionally, various swarm topologies, including global, ring, pyramid, and random configurations, were analyzed for their impact on optimization.

To further enhance the PSO's results, an improved initialization method was adopted. This involved a heuristic approach that prioritized time periods with higher energy prices and assigned maximum outflows accordingly. The Random Biased Optimization (RBO) method was then applied, introducing controlled randomness into the initialization process to generate diverse initial solutions (Juan et al., 2009). This combination of strategies allowed for more robust and efficient optimization of the HRIO problem.

## **7 REFERENCES**

Bernardes J, Santos M, Abreu T, Prado L, Miranda D, Julio R et al (2022) Hydropower operation optimization using machine learning: a systematic review. *AI* 3(1):78–99. <https://doi.org/10.3390/ai3010006>

Bratton, D., & Kennedy, J. (2007). Defining a standard for particle swarm optimization. In *Proceedings of the 2007 IEEE Swarm Intelligence Symposium* (pp. 120-127). IEEE. <https://doi.org/10.1109/SIS.2007.104>

- Castro-Freibott, R., García-Castellano Gerbolés, C., García-Sánchez, A. et al. MILP and PSO approaches for solving a hydropower reservoirs intraday economic optimization problem. *Cent Eur J Oper Res* (2024). <https://doi.org/10.1007/s10100-024-00934-z>
- Commission E (2017) Commission regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing. *Off J Eur Union* 312:6–53
- Guedes LSM, De Mendonca Maia P, Lisboa AC, Vieira DAG, Saldanha RR (2017) A unit commitment algorithm and a compact milp model for shortterm hydro-power generation scheduling. *IEEE Trans Power Syst* 32(5):3381–3390. <https://doi.org/10.1109/TPWRS.2016.2641390>
- Gurobi Optimization, LLC. (2020). Gurobi optimizer: Reference manual. Gurobi Optimization. Retrieved from <https://www.gurobi.com/documentation/>
- Helwig, M. (2010). Particle swarm optimization: An introduction and survey. *Computer Science Review*, 4(2), 29-57. <https://doi.org/10.1016/j.cosrev.2010.02.001>
- Juan AA, Faulin J, Ruiz R, Barrios B, Gilibert M, Vilajosana X (2009) Using oriented random search to provide a set of alternative solutions to the capacitated vehicle routing problem. In: *Operations research and cyber-infrastructure*. Springer, pp 331–345
- Juan, J. R., & Zhang, J. (2009). Randomized optimization algorithms and their applications. *European Journal of Operational Research*, 194(2), 299-307. <https://doi.org/10.1016/j.ejor.2007.11.014>
- Kennedy J, Eberhart R (1995) Particle swarm optimization. In: *Proceedings of ICNN'95—international conference on neural networks*, vol 4, pp 1942–1948
- Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of the IEEE International Conference on Neural Networks* (pp. 1942-1948). IEEE. <https://doi.org/10.1109/ICNN.1995.488968>
- Kumar V, Yadav S (2022) Multi-objective reservoir operation of the ukai reservoir system using an improved jaya algorithm. *Water Supply* 22(2):2287–2310
- Mäkelä, M., & Kallio, J. (2015). Hydropower optimization: A survey on methodologies and case studies. *Energy Conversion and Management*, 95, 373-383. <https://doi.org/10.1016/j.enconman.2015.02.004>
- Matheussen BV, Granmo O-C, Sharma J (2019). Hydropower optimization using deep learning. In: *Advances and trends in artificial intelligence from theory to practice: 32nd international conference on industrial, engineering and other applications of applied intelligent systems, IEA/AIE 2019, Graz, Austria, July 9–11, 2019, proceedings 32*, pp 110–122
- Miao Y, Qiu Z, Zhang X, Jiang Y, Pan J, Liu Y et al (2021) Effects of a water hammer and cavitation on vibration transients in a reservoir-pipe-valve system. *J Theor Appl Mech*. <https://doi.org/10.15632/jtam-pl/141335>
- Miranda LJV (2018) PySwarms, a research-toolkit for particle swarm optimization in python. *J Open Source Softw*. <https://doi.org/10.21105/joss.00433>
- Rodriguez JA, Anjos MF, Côté P, Desaulniers G (2018) MILP formulations for generator maintenance scheduling in hydropower systems. *IEEE Trans Power Syst* 33(6):6171–6180. <https://doi.org/10.1109/TPWRS.2018.2833061>
- Shi, Y., & Eberhart, R. C. (2001). Fuzzy adaptive particle swarm optimization. In *Proceedings of the 2001 Congress on Evolutionary Computation* (Vol. 1, pp. 101-106). IEEE. <https://doi.org/10.1109/CEC.2001.934374>
- Wolsey, L. A. (1998). *Integer programming*. Wiley-Interscience.
- Zhang R, Zhou J, Ouyang S, Wang X, Zhang H (2013) Optimal operation of multi-reservoir system by multi-elite guide particle swarm optimization. *Int J Electr Power Energy Syst* 48(1):58–68. <https://doi.org/10.1016/j.ijepes.2012.11.031>