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A particle swarm optimisation-based decision-support tool for efficient sizing of hydrogen systems in hydropower plants

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ABSTRACT

The integration of hydrogen technologies with renewable energy sources, such as hydropower, enhances the potential of green hydrogen production while maintaining electricity generation. This paper presents a method for optimally sizing a hydrogen system within a hydropower plant, enabling the cogeneration of green hydrogen and electricity. A decision-support tool based on particle swarm optimisation is developed to balance technical and economic factors, including hydrogen demand, water reserves, electrolyser efficiency, installation costs, and energy-market prices. The approach is applied to a case-study hydropower plant, utilising excess hydropower and photovoltaic electricity to produce hydrogen. The tool successfully optimises multiple objectives, such as income maximisation and hydrogen production targets, demonstrating its potential for integrating hydrogen systems into renewable energy frameworks. This work highlights a viable pathway for advancing the adoption of hydrogen technologies in sustainable energy systems.

1. Introduction

In response to climate change and the push for sustainability in the renewable-energy sector, significant efforts are underway to research and develop alternative energy sources and fuels. Among these, "green" hydrogen production has emerged as a priority for the European Union, which aims for Member States to collectively produce and import 20 million tonnes of hydrogen by 2030 [1]. Hydrogen is poised to play a crucial role in the decarbonisation of global energy systems, but its sustainability is heavily influenced by production methods. Advances in hydrogen system (HS) technology over the past decade have made the production of green hydrogen more feasible, with improvements in durability, flexibility, safety, and maintenance requirements. When powered by renewable energy sources, HSs generate green hydrogen with zero CO_2 emissions [2]. The renewables industry has experienced substantial growth [3–5] driven by increased production efficiency, reduced costs, and the emergence of new market players [6]. Hydropower, combined with HSs, can play a central role in decarbonising society. Hydropower plants (HPPs) are characterised as stable and reliable sources of electric energy. Leveraging their consistent water flow, these plants offer an opportunity for green-hydrogen production during regular operation because HPPs can provide excess, dispatchable electricity to produce it [7]. Utilising the excess (i.e., wasted) hydro energy in HPPs is an emerging strategy [8] and experts estimate that additional technological approaches can significantly increase hydropower annual energy generation [9]. Some studies have already demonstrated the potential to enhance the capacity utilisation of HPPs by generating and storing green hydrogen from excess hydro energy during off-peak periods and periods of high-water inflow, such as the rainy season [10]. Additionally, integrating HSs with photovoltaic (PV) fields and HPPs allows for the efficient use of excess energy [11], further contributing to grid stability and renewable energy storage.

Therefore, cogeneration of electricity and hydrogen in a HPP is the subject of intensive research. The authors in Ref. [10] consider that two fundamental approaches can be employed to estimate the potential for green hydrogen production from hydropower. The first approach assumes that a certain percentage of the available hydropower potential is dedicated to the green hydrogen production. The second approach, which is also used in our article, assumes the hydrogen production based on the excess electricity that would otherwise be curtailed or underutilised due to prescribed timetable, decreased demand or increased water inflows during the rainy season in run-of-river HPPs. Recent studies employing this second approach have shown that the hydrogen production from excess hydropower meets the principles of the circular economy [12] and is a significant opportunity for profit increase [13].

Despite the progress, challenges persist, particularly in optimising/sizing HS design and ensuring strong economic returns [14,15].

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Abbreviations:

HS	hydrogen system
HPP	hydropower plant
CapEx	capital expenditures
OpEx	operational expenditures
MCDA	multi-criteria decision analysis
ML	machine learning
P2G	power-to-gas
PV	photovoltaic
RUL	remaining useful life
PSO	particle swarm optimisation
HSCE	Hydrogen-System-Configuration Explorer
HSCO	Hydrogen-System-Configuration Optimiser

Although scaling up production is expected to reduce costs [16], the impact of capital expenditures (CapEx) and operational expenditures (OpEx) on total production costs remains complex. This has created the need for advanced decision-support tools to assist in the design, analysis, and optimisation of HSs [17–19]. These tools enable developers to make informed decisions about hydrogen infrastructure, considering the technical, economic, and environmental impacts [20].

A brief overview of relevant literature shows that decision-support tools have become critical in designing and optimising HSs, helping stakeholders evaluate technical, economic, environmental factors [17–21] and they address key considerations such as component selection, scalability, techno-economic analyses, and environmental impacts. The development of decision-support tools for HS sizing is progressing rapidly, benefiting from advanced modelling techniques such as multi-criteria decision analysis (MCDA) [22], optimisation algorithms [23,24], and machine learning (ML) [25]. These tools are designed to address the complexities of HS design, including interactions between components and scales. Furthermore, there is growing recognition of the importance of integrating HSs with other energy systems, such as electricity and natural-gas grids. This has led to the development of hybrid energy system design tools [26–29] and other system optimisation approaches [30–32]. However, significant challenges remain, including long-term modelling accuracy, cost reduction, and accounting for policy and market changes. While these tools are becoming more sophisticated, their real-world application is still in its infancy, requiring further improvements in usability, accessibility, and scalability.

The article's key novelty is the use of the particle swarm optimisation method (PSO) for the proper sizing of the HS in a HPP with available surplus hydropower for the cogeneration of electricity and hydrogen. The developed decision-support tool can improve the design of the HS for green-hydrogen production in HPPs. By using real data on water accumulation and integrating the production process, hydrogen technology modelling and an advanced optimisation method, the tool can assist with HS design and a techno-economic evaluation of its operation before any implementation. Innovations in decision-support tools, such as the application of PSO method, presented in the article, enable more accurate sizing of critical HS components such as electrolysers and hydrogen storage. By addressing technical, economic, and environmental challenges, the developed tool provides a pathway for more effective deployment of HSs.

The article is structured as follows: The *Introduction* highlights the importance of utilising surplus water energy for the production of green hydrogen and indicates the possibilities of optimising its production with the appropriate sizing of the HS. The *Methodology* introduces a PSO-based approach for optimising cost and efficiency, applied to a real-world case study. The *Results* demonstrate sizing improvements, while the *Discussion and Conclusions* validate the tool's effectiveness and suggest future research directions.

2. Methodology

2.1. Problem formulation

Modelling and simulation involve defining the mathematical models of the key components of the HS, including the HPP model, the electrolyser model, the hydrogen-storage model, the PV field model, the HS remaining-useful-life (RUL) model, and the economic model. Since an analytical calculation of the optimal parameters for such a system is not feasible, a computer simulation of the system's operation is employed. This approach allows for the evaluation of results and enables PSO-based automatic searches for the optimal HS parameters.

When designing a cogeneration system for electricity and hydrogen production in a HPP setting, several critical factors must be considered to meet the primary goal of fulfilling the prescribed electricity production timetable while generating green hydrogen from excess hydro energy. The sizing of a HS that operates only during periods of excess hydro energy requires a thorough evaluation of the hydrogen demand, the water-accumulation levels, the type and efficiency of the electrolyser, the hydrogen-storage capacity, and the integration of the system's components [33].

The design of a HS also involves selecting the appropriate components and balancing the costs, as the CapEx and OpEx expenses increase with the system's size and capacity. To ensure economic viability, minimising these costs is essential, as they directly influence the profitability of hydrogen production.

Our previous publications [34,35] introduced first attempts to explore the cogeneration of electricity and hydrogen in a HPP case-study environment. In Ref. [36] we proved that utilising excess hydro energy can improve the profitability of HPPs and support applications such as energy storage, grid stability, and hydrogen production. In Ref. [37] we described the integration of a HS into the regular operation of a run-of-river HPP to produce green hydrogen from excess hydro energy. This document proposes a method for optimising the hydrogen-production equipment, considering operational constraints, equipment costs, and market prices for electricity and hydrogen. A techno-economic model is presented, which is incorporated into a decision-support tool for sizing the HS.

A decision-support tool can be instrumental in optimising HS sizing by considering both the technical factors, such as the HPP's power output, the water-inflow dynamics, the electricity-consumption patterns, and the anticipated hydrogen demand. On the economic side, it considers factors like hydrogen-production costs, electricity and hydrogen market prices, and the potential revenue from sales. The developed tool relies on a real-data-based mathematical model that represents the entire system, including the process model for both the HPP and HS, an economic model, and a control system for coordinating hydrogen production [36]. The system model in Fig. 1 represents an integrated system for hydrogen production, combining key components for water flow management, energy generation (HPP and PV), and HS optimisation. For description of system model parameters refer to Table 1.

The key interactions between the sub-models and parameters include the system optimising energy utilisation by directing excess electricity from the HPP and PV field towards hydrogen production. Additionally, the economic and operational models ensure the cost-effective and efficient integration of hydrogen generation with renewable energy sources. Furthermore, the control system and the RUL model maintain system stability and enhance component longevity by dynamically monitoring performance and adjusting operations as required.

For a mathematical simulation, a comprehensive model of the entire process is required to enable the numerical simulation on a computer, eliminating the need for a real physical process. The simulation model mimics the real system and calculates the operational results, such as mass flows, energy flows, and financial flows, as they would occur in an actual system. The mathematical model evaluates the system's

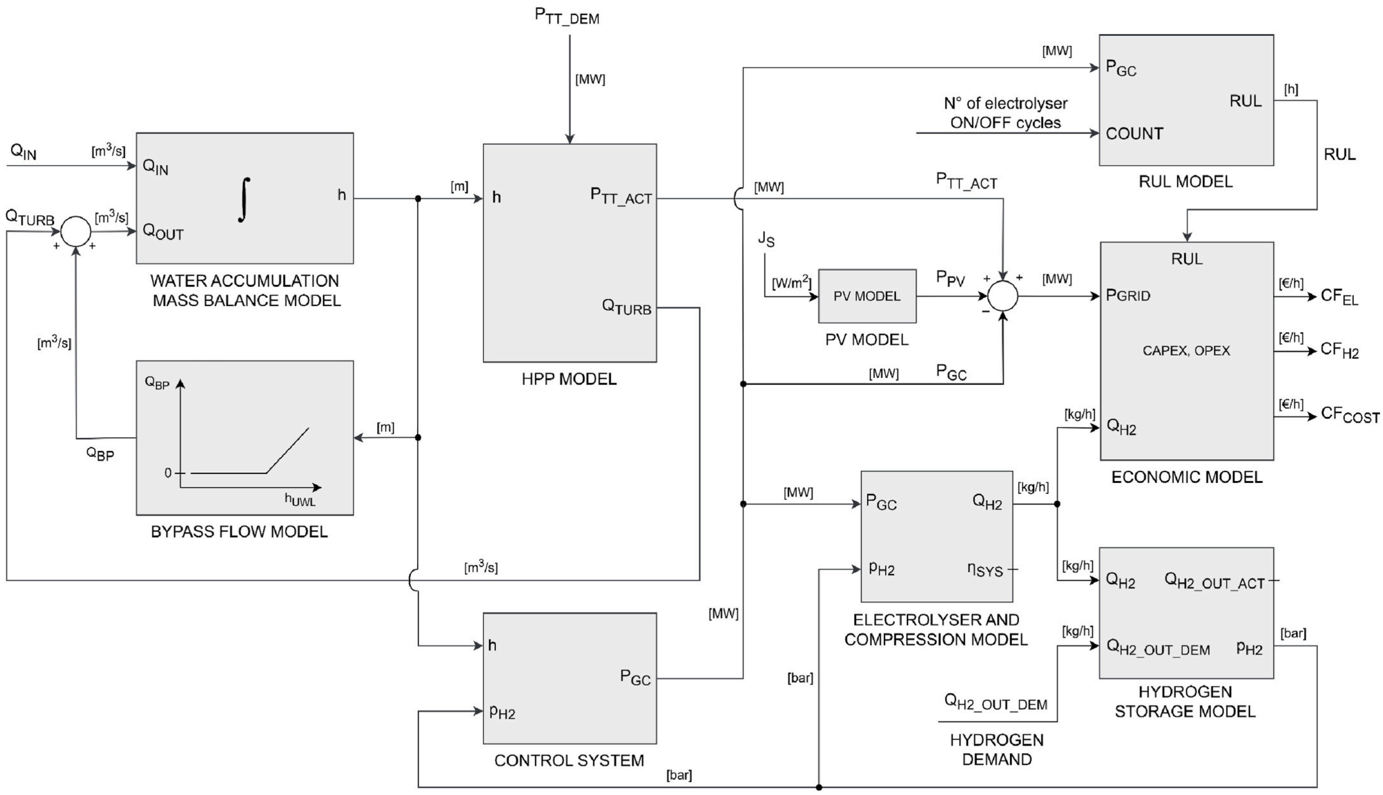

Fig. 1. Block scheme of the entire system model used in optimisation procedure.

Table 1
Description of model's main parameters.

Parameters	Parameter description	Units
Q_{IN}	Water inflow	m^3/h
Q_{OUT}	Water outflow	m^3/h
Q_{TURB}	Water-turbine flow	m^3/h
Q_{BP}	Water-bypass flow	m^3/h
Q_{H2}	Hydrogen-production flow rate	kg/h
$Q_{H2\_OUT\_DEM}$	Demanded hydrogen-output flow	kg/h
$Q_{H2\_OUT\_ACT}$	Actual hydrogen-output flow	kg/h
h	Head	m
h_{UWL}	Upper water level	m.a.s.l.
P_{TT_DEM}	Demanded generated power according to timetable	MW
P_{TT_ACT}	Actual generated power according to timetable	MW
P_{GC}	Hydrogen generation and compression power	MW
P_{PV}	Power generated by PV field	MW
P_{GRID}	Power delivered to grid	MW
η_{SYS}	HS's operating efficiency	%
J_S	Solar irradiance	W/m^2
p_{H2}	Current pressure in the hydrogen storage tank	bar
CF_{EL}	Positive cash flow generated by selling electrical energy	€/h
CF_{H2}	Positive cash flow generated by selling hydrogen	€/h
CF_{COST}	Negative cash flow incurred by HS CapEx and OpEx	€/h
RUL	The remaining useful life of the HS	h

performance over a selected time period. Different variants of the HS, with varying technical parameters, can be tested through this simulation process. The developed HPP model relates upper and lower water levels, water-flow rate, and generated electrical power. The water-accumulation, mass-balance model connects the input/output flow rates with the water levels in the reservoir. The model of the PV system estimates the electrical power generation based on the size of the plant and the solar irradiance data [37]. The model of the electrolyser links the input electric power to the hydrogen mass flow and the thermal power, factoring in the electrochemical and compression losses. The hydrogen-storage model relates hydrogen flow rates to the amount of hydrogen stored, expressed in terms of mass, thermal energy, and pressure. The hydrogen-compression model connects the flow rate and pressure to the electrical power consumed during compression. The RUL model estimates the RUL based on age, usage and system on/off cycles. Lastly, the economic model assesses the system's financial cash flows and calculates actual hydrogen production costs.

Once developed and verified, the decision-support tool can be used for tasks such as designing a system, optimised for different cogeneration scenarios, determining optimal component sizes, and evaluating the economic impact of various operational strategies. By simulating these scenarios, the tool helps to reduce the investment costs, lowers the hydrogen-production expenses, and enhances the financial sustainability of the HS investments.

As described above, the underlying model provides numerous physical and economic outputs and aggregated residuals, that can be used in optimisation. By including desired residuals in the optimisation cost function, the tool finds the HS setup with best-fitting parameters. Moreover, for detailed operation inspection, the tool provides the time-plots of operational parameters for the designed setup over a selected time period.

The next section details the description and application of this HS-sizing tool in the context of a case-study HPP.

2.2. Hydrogen-System-Configuration Optimiser

In our previous work [37] we introduced a design-support tool called the *Hydrogen-System-Configuration Explorer* (HSCE), which estimates near-optimal parameters for the installation of a HS in a given case-study HPP. The HSCE employs a series of simulation runs over a defined range of process parameters, enabling efficient and transparent sizing of the HS's main components. This method belongs to a class of exhaustive (also called brute-force) optimisation methods, which systematically explore all the potential combinations of parameters in search of the best solution.

While the HSCE has proved to be a valuable tool for design, insight and decision-making, several features can be improved.

- Due to the parameter-space discretisation, the accuracy of the indicated optimal solution is limited and sometimes more accurate results are needed.
- Only a limited number of parameters subjected to optimisation can be included in the simulation to keep the computation effort acceptable. If the number of optimised parameters is increased, the number of parameter combinations increases progressively and so does the computational burden and the simulation time.
- In the case when a parameter that is not the subject of the optimisation is changed, the whole set of simulations must be repeated, which is time consuming and can in some cases represent a drawback.

To overcome these challenges and to refine our search strategy we introduce an alternative system-design tool called the *Hydrogen-System-Configuration Optimiser* (HSCO). This tool is based on one of the heuristic optimisation methods, specifically the PSO method [38–40]. PSO was selected due to its intuitive algorithm, which can be easily understood by engineers without specialised expertise in computational optimisation. Alternative methods, such as genetic algorithms, simulated annealing and many others [41], were also considered, but PSO stood out because of its simplicity and effectiveness.

In general, the mathematical optimisation problem is the problem of finding the best solution for the defined objective function $f(\boldsymbol{x})$ from all feasible solutions. This means that the optimisation method searches for the parameter vector $\boldsymbol{x}$, which gives the minimum (or maximum) function evaluation of $f(\boldsymbol{x})$, so that the assumed constraints of the vector $\boldsymbol{x}$ are not violated. Objective functions are related to one or more goals, e.g., minimisation of cost or energy consumption or maximisation of financial outcome, while constraints are related to physical or virtually imposed constraints.

Note that in presented case, $f(\boldsymbol{x})$ is not an analytical function of the parameter vector $\boldsymbol{x}$. For a given vector of parameters $\boldsymbol{x}$, the function $f(\boldsymbol{x})$ is evaluated by performing a real-data simulation run of the complete process over the desired time interval (e.g., 1 year) and then calculating the value of desired objective function $f(\boldsymbol{x})$. In our case, various objective functions are possible, and they represent different technical or economic key-performance indicators of the HS's operation.

2.3. Particle-swarm optimisation algorithm

The PSO algorithm can find the optimal solution (either local or global) with a relatively small number of system operation simulations [42]. It consists of a set of proposed solutions (particles) with a random initial position. Each particle represents an instance of parameter vector $\boldsymbol{x}$. The algorithm solves an optimisation problem by using a population (a swarm) of candidate solutions (particles) and by moving these particles around in the search space according to simple mathematical formula over the particle's position and velocity.

The algorithm involves two equations, commonly referred to in the literature as the *velocity* and *position* equations. In both, i represents the index of an individual particle and n represents the number of current iterations.

The *velocity equation* (see Eq. (1)) [43], is used to update the velocity of each particle in the n-th iteration by using the computed values of the individual-particle ($\boldsymbol{pbest}^i$) and global ($\boldsymbol{gbest}$) best solutions and its current position $\boldsymbol{x}^i(\mathrm{n})$. The velocity equation in fact represents an increment from the current position $\boldsymbol{x}^i(\mathrm{n})$ to the new position $\boldsymbol{x}^i(\mathrm{n+1})$.

$$\boldsymbol{v}^i(n+1) = w \bullet \boldsymbol{v}^i(n) + c_1 \bullet r_1 \bullet \left(\boldsymbol{pbest}^i(n) - \boldsymbol{x}^i(n)\right) + c_2 \bullet r_2 \bullet \left(\boldsymbol{gbest}(n) - \boldsymbol{x}^i(n)\right) \tag{1}$$

In Eq. (1), c_1 is the self-adjustment weight, which determines the influence of a single particle, and c_2 is the social adjustment weight, which determines the influence of the entire swarm. These are acceleration parameters, compounded with user-defined gains r_1 and r_2, which range from 0 to 1. These parameters control the balance between refining the particle's own search result and recognising the swarm's search result. The parameter w is an inertia parameter and takes a value between 0 and 1, determining the extent to which the particle retains its previous velocity.

The *position* equation (see Eq. (2)) [43], is used for updating each particle's position using the calculated velocity from Eq. (1):

$$\boldsymbol{x}^i(n+1) = \boldsymbol{x}^i(n) + \boldsymbol{v}^i(n+1) \tag{2}$$

Each particle's movement in PSO is influenced by its local best-known position, but it is also guided towards the best-known positions in the search space, which are updated as better positions are found by other particles. Fig. 2 illustrates the shift of an individual particle in one iteration towards the global solution.

As the number of iterations increases, the convergence rate towards the best-known position improves. Optimisation is complete when the solution is located at a point that appears to be a local or global minimum. In multimodal optimisation, PSO balances exploration and exploitation to navigate complex landscapes and avoid local minima. The global minimum is the best solution found by the entire swarm, while the local minimum is the best solution found by an individual particle in its vicinity. PSO strives to balance exploration (seeking the global minimum) and exploitation (refining local minimum solutions) through interactions and updates based on both individual and neighbour best positions.

In our case the PSO algorithm was implemented in *MATLAB* using the *Optimisation Toolbox* and the *fmincon* function to perform the minimisation process, taking into account the constraints. An automation script was also developed (*optim_script*, [44]), which starts the simulation of the entire system model for a given set of system parameters, calculates the selected residuals and enables the automatic search for the optimum of the selected objective function. The PSO algorithm's design-specific parameters (e.g., population and control) require proper tuning to impact behaviour and performance.

The essential steps of the whole iterative optimisation procedure are shown in Fig. 3.

2.4. Case-study HPP

The described HSCE was used for sizing the HS of one of the Slovenian HPPs [37]. The case-study involves a 50-MW run-of-river-type

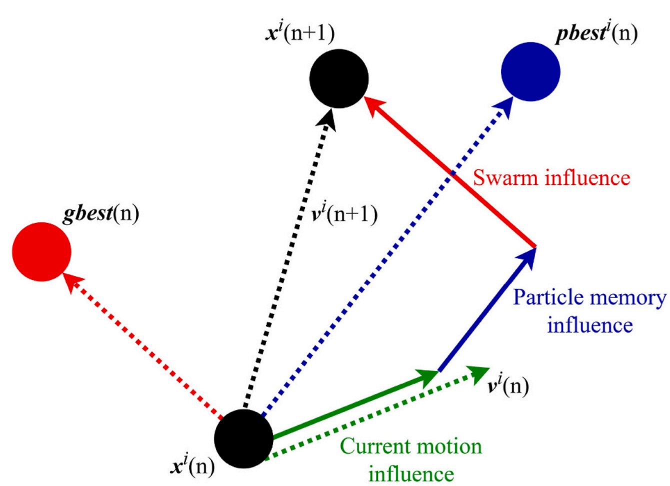

Fig. 2. Schematic individual particle shift in n-th iteration for two-dimensional x [30].

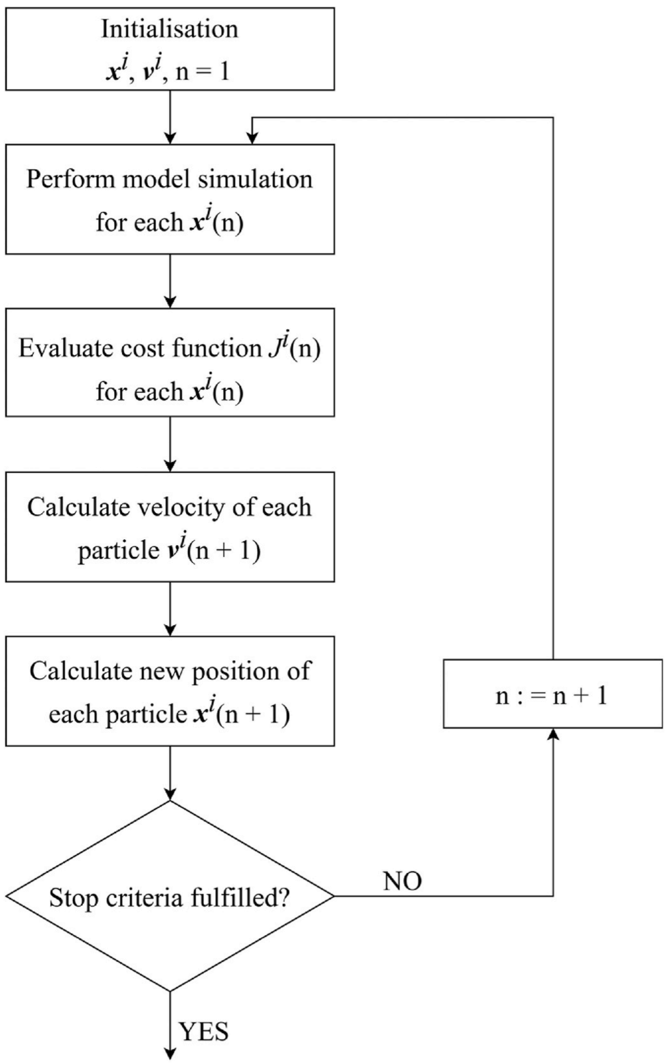

Fig. 3. Graphical presentation of the *optim_script*.

HPP, which is the last in a cascade of five HPPs, and features a low-capacity water reservoir of approximately 3,400,000 cubic meters. This HPP supplies electricity according to a pre-set timetable defined by the national system operator. The timetable is based on various factors, including models of the production capacity, forecasted consumption, current water levels, river-flow conditions, weather forecasts, and the system operator's strategy. The inherent uncertainty in these model inputs affects the timetable, necessitating a small reserve of water potential for exploitation. Consequently, some hydropower remains unused, leading to higher water accumulation in the reservoir. Periodically, this excess hydropower can be harnessed for electricity generation that is used for hydrogen production.

A specialised control algorithm was developed to transform the excess hydropower into the electricity required for the HS's operation [36]. The HS's load depends on the current water accumulation and the pressure in the hydrogen-storage tank. The calculated, assigned electrical power for the HS allows the electrolyser to operate most of the time in the range 20–80 % of its nominal power, as the electrolyser operates most efficiently in this range. The HS is only shut down in cases of very low water accumulation in the reservoir or when the hydrogen-storage tank is full. Using this operational strategy naturally results in a reduction of water accumulation in the HPP reservoir, as shown in Fig. 4.

Additionally, the case-study HPP is equipped with a PV field with a nominal capacity of 6 MW. If more hydrogen production is required or if there is a need to maintain high water levels in the reservoir, some of the electricity from the PV field can be used to support the HS's operations.

An agreement between the administration of the HPP and the local city administration stipulates that the green hydrogen produced will be used to power hydrogen-fuelled suburban buses. A 12-m-long hydrogen-powered bus consumes approximately 9 kg of hydrogen per 100 km. With an average daily travel distance of 400 km per bus, the daily green hydrogen production from the case-study HPP would be sufficient to fuel four such buses each day.

2.5. Optimised parameters and objective functions

The parameters that are the subject of the optimisation represent the components of vector $\boldsymbol{x}$; ($\boldsymbol{x} = [P_{EL\_SYS}, P_{PV\_INST}, V_{STOR}]$), where each element corresponds to a specific system variable. The range of each parameter, which determines the limits of the optimisation process, is provided in Table 2. These ranges define the possible values each

Table 2
List of optimised parameters and their constraints.

Parameter	Description	Range	Units
P_{EL_SYS}	Nominal power of the HS	[0.25 … 1.5]	MW
P_{PV_INST}	Nominal power of the PV field	[0 … 6]	MW
V_{STOR}	Volume of the hydrogen-storage tank	[10 … 80]	m^3

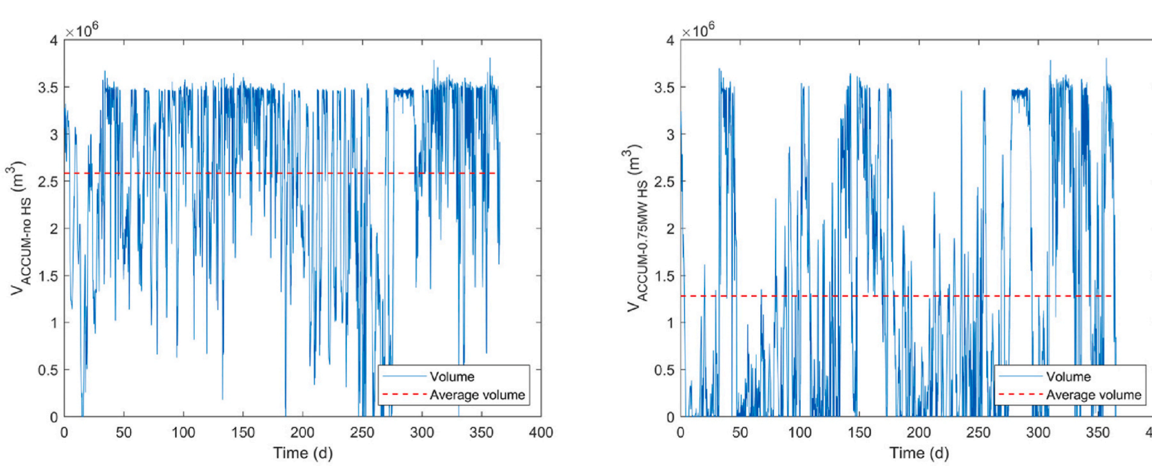

Fig. 4. Average annual volume of water accumulation in case-study HPP reservoir for the example based on 0.75-MW HS and 20 m^3 storage tank: (a) without HS operation and (b) with HS operation.

component of the vector $\boldsymbol{x}$ can take during the optimisation process to achieve the desired outcomes.

In the following section, three examples of objective functions are defined to address the technical and economic key performance indicators. It should be noted that various other forms of objective functions can be employed depending on the specific priorities set during the design of the HS and related techno-economic targets (such as e-flows, denivelation minimisation, HS utilisation rate, etc.). The choice of objective function allows for flexibility in addressing different performance targets, such as minimising costs, maximising energy efficiency, or balancing supply and demand. This adaptability ensures that the HS can be tailored to meet specific operational or financial objectives.

To streamline the computational complexity, the simplified system model was employed, focusing on key characteristics such as mass and energy balances and system efficiencies. The HPP and electrolyser models are static, while the water-accumulation and hydrogen-storage models incorporate dynamic elements, allowing for a consideration of the mass and energy flows. The most critical inputs to the system model are the electrical power demand according to the timetable P_{TT_DEM}, the hydrogen demand $Q_{H2\_OUT\_DEM}$, the water inflow to the water accumulation Q_{IN} and the solar radiation J_S.

For all the scenarios, the hydrogen selling price (SP_{H2}) is set at 8 €/kg, with the maximum tank pressure capped at 350 bar. The actual costs of hydrogen production are estimated based on the technological equipment used. The hydrogen production target for the first scenario was set at a maximum of 320 kg per day.

3. Results

3.1. Optimisation of income

As the first scenario, the objective function is defined as the annual income from the hydrogen production ($J_1 = -Income_{H2}$):

$$J_1 = -Income_{H2} = -\int_0^{t_{end}} \dot{m}_{IN}(t) \bullet (SP_{H2}(t) - PC_{H2}(t)) \bullet dt \tag{3}$$

A negative value for $Income_{H2}$ is applied in the optimisation process, as the selected *MATLAB* procedure uses minimisation criteria by default. By minimising a negative income value, the algorithm effectively maximises the income based on the parameter constraints defined in Table 2.

The solution to this optimisation problem provides the optimal configuration of the HS that results in the highest annual income generated from hydrogen production in the case-study HPP.

During the iterative optimisation process, key output parameters are monitored and displayed, as shown in Table 3, to track progress and evaluate the performance of different configurations.

The optimisation results show that the optimal configuration for the highest annual income, taking into account the installation costs of the HS and the current operating regime of the case-study HPP, is as follows (see Table 4):

Under these conditions, the annual hydrogen production reaches 76,601 kg, with a corresponding income of 349,290 €/y and a utilisation rate for the HS of 75.01 %. It is important to know that in this case the average hydrogen consumption is approximately 210 kg/d, meaning the targeted hydrogen demand of 320 kg/d is not met, though this is not penalised. Additionally, the maximum income does not necessarily equate to the maximum production of hydrogen, but rather reflects the optimal balance between minimising the system costs and maximising the revenue from hydrogen sales.

Table 3
Selected important output parameters of the model.

Parameter	Parameter Description	Units
m_{H2_PROD}	Annual mass of produced hydrogen	kg/y
PC_{H2}	Production cost of hydrogen	€/kg
c	Utilisation rate of the HS	%
$Income_{H2}$	Income from the production of hydrogen	€/kg

Table 4
PSO algorithm results for J_1 objective function.

Parameter	Parameter Description	PSO result	Units
P_{EL_SYS}	HS's maximum power	0.9060	MW
P_{PV_INST}	PV's nominal (installed) power	0	MW
V_{STOR}	Volume of the hydrogen-storage tank	28.0098	m^3

Best objective function value and its search is presented in Fig. 5(a). The term *Stall iteration* refers to an iteration where the particles were moved, but the best solution of the best particle was not better than the current best global solution. Fig. 5(b) shows the "ranges of parameters", which is a characteristic plot of the PSO algorithm and illustrates the convergence of the optimised parameters during the iterations. As mentioned earlier, in each iteration a number of parameter vectors (particles) are shifted in search of the optimal solution. Ideally, after a number of iterations, all the particles should converge to the same global optimal solution, if it exists for a given optimisation problem.

In this case, Fig. 5(b) contains three plots, as three parameters are being optimised (P_{EL_SYS}, P_{PV_INST}, V_{STOR}). Each plot shows the range of a particular parameter, defined as the difference between the current maximum and minimum values of that parameter across all the particles. Initially, these ranges are large, as the parameter vectors (particles) are randomly distributed over the entire parameter space. Over the course of the iterations, if the parameters converge towards a global optimum, zero indicating that the optimum has been found. The y-axes of the plots are represented on a logarithmic scale to effectively represent the wide potential ranges of parameters.

3.2. Optimisation of hydrogen System's size to achieve targeted hydrogen production

In the next scenario of optimal sizing for the HS components, the goal is to determine the optimal size of the HS equipment that meets a predefined annual target for hydrogen production. Please note, that in this scenario the costs of PV field and HS's installation are not considered. The corresponding objective function can be defined as:

$$J_2 = f(x) = \left(Q_{H2\_OUT\_DEM} \bullet 365\ [d] - m_{H2\_PROD}\right)^2 \tag{4}$$

where in our case the predefined hydrogen-production target ($Q_{H2\_OUT\_DEM}$) was set at a maximum of 160 kg of hydrogen per day.

The optimisation results indicate that the (local) optimal configuration for achieving the targeted annual hydrogen production, while respecting only the current operating regime of the case-study HPP, is as follows (see Table 5):

In this configuration, the hydrogen production reaches the predefined hydrogen production of 58,400 kg/y (160 kg/d). The detailed results of the optimisation process are presented Fig. 6.

However, the corresponding income in this scenario is negative (−94,120 €/y), primarily due to the high costs of the necessary HS equipment, the high installation costs of the PV field, and the low targeted daily volume of hydrogen production. The reason for this is the selected criterion function, which does not consider the economic aspect of the operation. To address this problem, additional criteria should be integrated into the objective function, which balances both the technical performance and the economic feasibility. This integration will be explored further in the next Subsection 3.3, where economic considerations are added to optimise the overall system performance.

In our case, another possibility to reach the targeted hydrogen production of 160 kg of hydrogen per day with positive yearly income can be achieved without using the excess energy from the PV field, relying solely on the excess hydro energy. In this scenario the optimisation

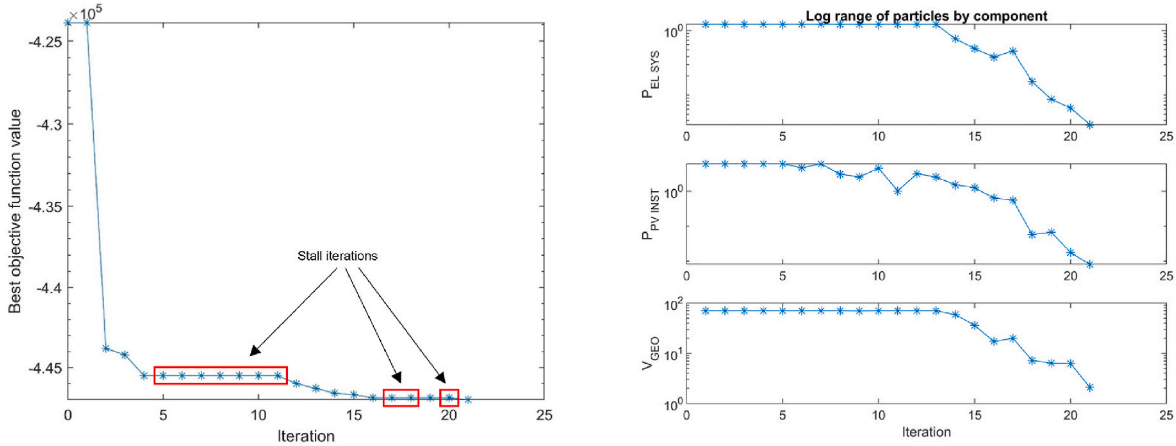

Fig. 5. (a) Values of the objective function J_1. (b) Parameter ranges: the top graph shows the maximum power of the HS, the centre graph the nominal power of the PV field, and the bottom graph the volume of the storage tank.

Table 5
PSO algorithm results for J_2 objective function.

Parameter	Parameter Description	PSO result	Units
P_{EL_SYS}	HS's maximum power	0.3551	MW
P_{PV_INST}	PV's nominal (installed) power	6	MW
V_{STOR}	Volume of the hydrogen-storage tank	35.2141	m^3

results indicate that the optimal configuration for achieving the targeted annual hydrogen production is as follows (see Table 6):

In the configuration excluding the PV field, annual hydrogen production is maintained at 58,400 kg/y (160 kg/d), with the utilisation rate of the HS at 79.64 %. This configuration results in a positive annual income (213,785 €/y). However, the irregular availability of excess hydro energy for system operation necessitates the use of a larger electrolyser and a larger hydrogen-storage tank.

Generally, the parameter P_{PV_INST} is an optimised parameter. However, in this case, we have constrained both its upper and lower limits to 0, thereby excluding it from the optimisation process and fixing its value at 0 MW. The results are shown in Fig. 7.

3.3. Multi-objective optimisation

To balance the objectives of achieving both profitability and targeted hydrogen production the two objective functions are now combined into a new objective function. This is done by creating a linear combination of the two objective functions (see Eq. (5)), with each function being assigned its own weight (k_1, k_2). These weights allow for the prioritisation of one objective over the other, if needed.

$$J_3 = -k_1 \bullet \left(\frac{Income_{H2}}{Income_{H2\_MAX}}\right) + k_2 \bullet \left(\frac{m_{H2\_PROD} - Q_{H2\_OUT\_DEM} \bullet 365\,[d]}{Q_{H2\_OUT\_DEM} \bullet 365\,[d]}\right)^2 \quad (5)$$

To ensure that both objectives have equal impact on the overall optimisation, each objective function undergoes normalisation. This process ensures proper scaling, preventing discrepancies in units or magnitudes from distorting the results. Using normalisation, both profitability and hydrogen production are given a balanced influence, ensuring neither demand outweighs the other in the optimisation process.

In the equation the hydrogen-production target ($Q_{H2\_OUT\_DEM}$) is set as 160 kg per day, while the maximum annual income from hydrogen

Table 6
PSO algorithm results for J_2 objective function.

Parameter	Parameter Description	Result	Units
P_{EL_SYS}	HS's maximum power	0.4414	MW
P_{PV_INST}	PV's nominal (installed) power	0	MW
V_{STOR}	Volume of the hydrogen-storage tank	58.2813	m^3

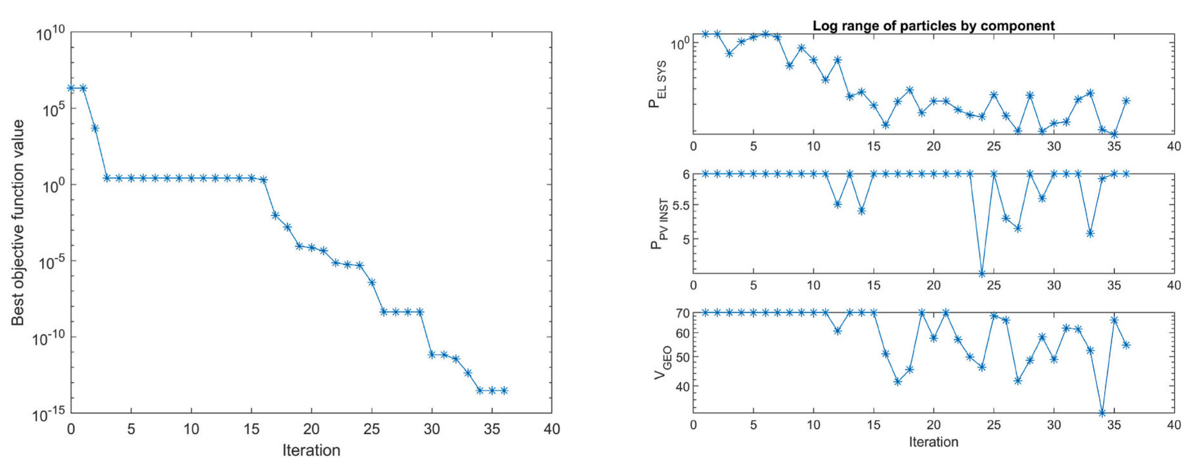

Fig. 6. (a) Values of the objective function J_2. (b) Parameter ranges: the top graph shows the maximum power of the HS, the centre graph the nominal power of the PV field, and the bottom graph the volume of the storage tank.

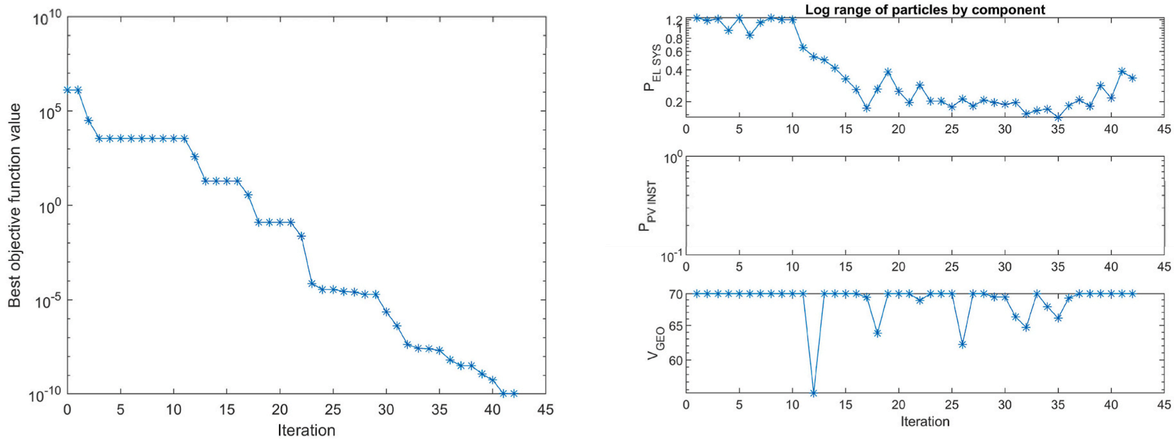

Fig. 7. (a) Values of the objective function J_2. (b) Parameter ranges: the top graph shows the maximum power of the HS, the centre graph the nominal power of the PV field, and the bottom graph the volume of the storage tank.

production ($Income_{H2\_MAX}$) is set as 425,000 €. The PSO algorithm is then applied with varying coefficients k_1 and k_2 to find the optimal balance between hydrogen production and profitability.

Table 7 presents the results of the PSO algorithm for different combinations of these coefficients, highlighting how the balance between maximising income and meeting production requirements can shift depending on the chosen weighting factors. This approach allows fine-tuning of the system design based on the relative importance of economic performance versus production targets.

The target hydrogen production in this scenario is 160 kg per day, which is equivalent to 58,400 kg per year. This value can be compared to the mass of produced hydrogen (m_{H2_PROD}) in Table 7 to assess how well the second objective function was fulfilled. As seen in the table, when the second objective function is strongly prioritised (with $k_1 = 0.1$ and $k_2 = 0.9$), the target value is most closely achieved.

When hydrogen demand is doubled to 320 kg/d, the possibility of exploiting electrical energy from the PV field becomes meaningful. Table 8 lists the PSO algorithm results for different coefficients k_1 and k_2. It is assumed that all the produced hydrogen is sold at a set price, not just the amount required to meet demand.

4. Discussion

Hydrogen is a promising energy carrier and is widely regarded as a key driver for the long-term green transition. However, current production methods, which rely heavily on the steam reforming of natural gas, do not align with long-term climate and energy goals. In contrast, green hydrogen produced through water electrolysis powered by renewable electricity offers high added value. This CO_2-emission-free process can play a crucial role in reducing carbon emissions, reducing local pollution, enhancing energy independence, and supporting sustainable development goals.

Given that HPPs are some of the most reliable sources of green electricity, incorporating also energy buffer, exploring the potential for cogenerating green hydrogen within these facilities is a logical step. However, such an upgrade requires the adoption of new technologies, where factors such as installation costs, optimal component sizing, and operational profitability are not yet fully assessed. In general, green-hydrogen production requires substantial new infrastructure to scale, and considerable investments in the distribution value chain.

So far, the focus was primarily on the development of the necessary equipment for a HS, while the economic aspects of its proper sizing in various environments have been on the side-line. Despite significant progress in optimal HS sizing, several challenges remain. One of the primary challenges is the integration of optimisation tools with real-time data and dynamic system conditions, which is crucial for an accurate and adaptive optimisation. Additionally, the complexity of HSs, with their multiple interacting components and scales, poses difficulties when creating comprehensive and scalable optimisation models.

Another challenge is the need for standardised methodologies and tools that can be widely adopted across different regions and applications. The diversity of hydrogen technologies and the varying maturity levels of these technologies make it difficult to develop universal optimisation tools. Moreover, the uncertainty related to future hydrogen demand, market conditions, and policy regulations adds complexity to the optimisation process.

This article demonstrates that the developed decision-support tool based on a PSO algorithm can enhance the design process of HSs. The simulations performed with this tool offer a comprehensive overview of various dimensioning options, aiding in more informed decision-making.

However, the PSO algorithm has some limitations. It can sometimes fall into a local optimum (premature convergence), especially in high-dimensional spaces, and so does not always guarantee a global optimum. Additionally, it exhibits a relatively slow rate of convergence during its iterations, and the simulation process can thus be time consuming.

Another drawback of presented case study is the use of fixed electricity and hydrogen prices in the applied economic model. Namely, the prices on the energy market are driven by multiple factors, leading to constant fluctuations. In this article, the prices of the energy sources are considered to be fixed during the simulation period, however, the model

Table 7
PSO algorithm results for J_3 objective function, changing various coefficients k_1 and k_2, with a target hydrogen production ($Q_{H2\_OUT\_DEM}$) of 160 kg per day.

Variables	k_1	k_2	Results				
			P_{EL_SYS} [MW]	P_{PV_INST} [MW]	V_{STOR_MAX} [m^3]	$Income_{H2}$ [€/y]	m_{H2_PROD} [kg/y]
	0.75	0.25	0.7352	0	19.2448	398,768	95,642
	0.50	0.50	0.6534	0	17.2494	392,050	83,529
	0.25	0.75	0.5119	0	14.1594	264,148	66,926
	0.10	0.90	0.4643	0	12.5328	296,324	59,235

Table 8
PSO algorithm results for the J_3 objective function, changing various coefficients k_1 and k_2, with a target hydrogen production ($Q_{H2\_OUT\_DEM}$) of 320 kg per day.

Variables	k_1	k_2	Results				
			P_{EL_SYS} [MW]	P_{PV_INST} [MW]	V_{STOR_MAX} [m^3]	$Income_{H2}$ [€/y]	m_{H2_PROD} [kg/y]
	0.75	0.25	1.4903	4.0361	35.3375	490,436	117,803
	0.50	0.50	1.2987	2.1954	31.4271	580,203	135,040
	0.25	0.75	1.2434	0.9107	30.3093	537,767	119,781
	0.10	0.90	1.2143	0.7674	29.0963	545,415	117,385

can use varying prices provided they are available as input data.

The future of HS optimisation lies in the continued development of advanced modelling techniques, the integration of artificial intelligence and machine learning predominantly in generating useful input data and predictions (price, weather), and the enhancement of decision-support tools. These advances will enable more accurate, scalable, and flexible optimisation solutions, capable of addressing the evolving needs of the hydrogen economy. Collaborative platforms and open-source tools are also expected to play an important role in optimal HS sizing. By fostering transparency and collaboration among researchers, industry players, and policymakers, these platforms can accelerate innovation and the adoption of best practices in HS design and operation.

5. Conclusions

The article introduces an approach to sizing a HS within a HPP, that would enable cogeneration of a limited amount of green hydrogen alongside regular production of electricity. The described HS demonstrates a novel approach for converting excess hydropower from a Slovenian HPP into green hydrogen. Through a specialised control algorithm, the system effectively operates the electrolyser within its optimal efficiency range, leveraging both hydropower and, optionally, solar energy. Optimisation analyses reveal trade-offs between maximising hydrogen production and profitability, with configurations influenced by parameters like electrolyser power, hydrogen-storage volume, and solar-field capacity. Multi-objective optimisation highlights the flexibility of the system to balance economic and technical goals. The results underscore the potential for integrating renewable energy sources to enhance the sustainability and financial viability of green hydrogen production.

CRediT authorship contribution statement

David Jure Jovan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gregor Dolanc:** Writing – review & editing, Project administration, Investigation, Funding acquisition, Conceptualization. **Boštjan Pregelj:** Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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