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ML-based energy management of water pumping systems for the application of peak shaving in small-scale islands

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A R T I C L E I N F O

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A B S T R A C T

This study introduces an energy management method that smooths electricity consumption and shaves peaks by scheduling the operating hours of water pumping stations in a smart fashion. Machine learning models are first used to accurately forecast the electricity consumed and produced by renewable energy sources on an hourly level. Then, the forecasts are exploited by an algorithm that optimally allocates the operating hours of the pumps with the objective to minimize predicted peaks. Constraints related with the operation of the pumps are also considered. The performance of the proposed method is evaluated considering the case of a Greek remote island, Tilos. The island involves an energy management system that facilitates the monitoring and control of local water pumping stations that support residential water supply and irrigation. Results indicate that smart scheduling of water pumps in a small-scale island environment can reduce the daily and weekly deviation of electricity consumption by more than 15% at no monetary cost. It is also concluded that the potential gains of the proposed approach are strongly connected with the amount of load that can be shifted each day, the accuracy of the forecasts used, and the amount of electricity produced by renewable energy sources.

1. Introduction

The proper operation of water supply systems is directly associated with the assurance of water accessibility to the population. Water and energy constitute two of the most vital resources and their integrated management can provide significant multifarious economic and environmental benefits in both sectors. In this respect, the United Nations Sustainable Development Goals (SDGs), and especially Goals 6 and 11, have identified the problem of ensuring availability and sustainable management of water for all, addressing specific actions to ensure access to safe water and focusing on resource efficiency improvement (UN, 2015). The aim is to implement an integrated water resources management system to support and strengthen the participation of local communities in improving water management by 2030. As of 2014, the annual energy consumption of the water sector accounted for around 120 Mtoe, globally. The largest part of the energy consumption is absorbed in the form of electricity, which corresponds to around 4% of the total global electricity consumption (Luna, Ribau, Figueiredo, & Alves, 2019). According to Carns (2005), energy consumption in the form of electricity is required for several processes in water supply systems, being necessary mainly for pumping, water filtration, flocculation, and feeding of coagulant and chlorine. Water demand is projected to increase by 44% by 2050 due to the growth of the manufacturing, thermal power generation, agriculture, and residential sectors. According to the Water–Energy Nexus report of the International Energy Agency (IEA), the availability of water is also becoming an issue of great importance due to the economic and population growth, as well as climate change, especially for emerging economies, intensifying the interdependency of water and energy in the coming decades (IEA, 2016).

Water companies and municipalities in general aim to guarantee the security of water supply, while also reducing the energy consumption and operational costs, as well as the environmental impacts associated to the whole process (Papapostolou, Kondili, & Tzanes, 2018). Several actions for improving the sustainability of the water sector have already been implemented (Papapostolou, Kondili, Zafirakis, & Tzanes, 2020),

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including on-site renewable energy sources (RES), among others, aiming to contribute to the decentralization and diversification of electric energy production (Ruangpattana, Klabjan, Arinez, & Biller, 2011). Besides that, more actions are being considered, like retrofitting the equipment of the water supply systems. However, such actions tend to include extensive financial costs and to require significant investments, setting insurmountable limitations in their implementation (Mankad & Tapsuwan, 2011). Another approach is to focus on the improvement of the pumping operation by enhancing the pumping control through optimization techniques. More specifically, digital and control techniques have emerged, like monitoring systems and advanced optimization modeling, which have the advantage of not requiring major investments like system renovations, making them more attractive (Kernan, Liu, McLoone, & Fox, 2017; Lange, Rueß, Nuß, Öchsner, & März, 2020; Wanjiru, Zhang, & Xia, 2016).

The problem of water resources management is even more crucial in small, remote areas like islands, because of the insufficient water resources and the high demand, mainly during the summer period due to increased tourism arrivals. A number of chronic problems which have not been resolved yet are the delayed planning in regional and national level and the insufficient strategy concerning the use of water for agricultural applications (Gikas & Angelakis, 2009). In this context, several smart energy management algorithms have been developed for load smoothing and peak shaving, based on dynamic modeling in specialized software systems implementing the proposed solutions, such as the APROS software (Chapaloglou et al., 2019) and the TRNSYS 17 simulation tool (Chua, Yang, Er, & Ho, 2014). Additionally, several studies have focused on directly coupling photovoltaic systems with water pumping systems (Padmavathi & Daniel, 2011), aiming either to achieve the most reliable and economical operation of the latter (Campana et al., 2015; Ghoneim, 2006), or the optimal sizing of stand-alone photovoltaic (PV) water pumping systems (Olcan, 2015; Yahyaoui, Atieh, Serna, & Tadeo, 2017).

This paper focuses on the smart energy management of remote island energy systems, putting a particular emphasis on the load peaks that can be shaved by optimally scheduling the operating hours of installed water pumping stations. In this context, the problem setting of this study can be formulated as follows: Given historical data about the total electricity consumed on the island and the corresponding RES-based production, the objective is to optimally schedule the operation of the island's water pumping stations. Specifically, the aim is to propose on a daily basis an hourly plan for operating the water pumping stations so that the peaks of the net load (i.e. total electricity consumption minus RES-based production) are minimized under a set of constraints related to the minimum operating hours of the water pumping stations that ensure water availability. This objective can be quantified through specific KPIs, which evaluate the daily and weekly deviation of the net electricity consumption at an island level. In this study, the proposed method is applied on the use case of Tilos, a small Greek island and municipality located in the Aegean Sea that, among others, involves distributed PV power production and a number of municipal water pumping stations.

The proposed peak shaving method provides a data-driven solution to the water supply system scheduling problem which is flexible in terms of operating hours and number of shiftable loads constraints and builds on the following key components:

- An ensemble of three machine learning (ML) models that forecasts electricity consumption by considering daily and monthly seasonal patterns of load, as well as trends.
- An ensemble of three ML models that forecasts PV-based electricity production by considering weather predictions, among other explanatory variables.
- A set of constraints related with the operating hours required by the pumping stations on a daily level to ensure water availability, as well as the flexibility of their operation.
- A heuristic optimization algorithm that shaves peaks in a dynamic way so that (i) the energy system of the island benefits from the electricity produced by RES and (ii) the operating hours of the pumps do not coincide with the island's electricity consumption peaks.

The innovation of the proposed method lies in its stand-alone architecture that requires no support from professional software simulation tools. The method is composed of two ensembles of three baseline forecasting models that are accurate, easy to implement, require a limited amount of data to be effectively trained, and are robust to overfitting and uncertainty, as well as a heuristic optimization algorithm that is flexible in terms of inputs and load shifting rules considered. Moreover, in contrast to existing peak shaving solutions that depend largely on battery energy storage systems (Uddin et al., 2020), the proposed method does not require storing energy to shave peaks, thereby being applicable to many isolated micro-grids. Finally, the proposed method tackles the problem of peak shaving from an innovative perspective that directly links water availability with energy conservation, providing also empirical evidence on how peak shaving gains are related with (i) the amount of load that can be shifted on a daily basis, (ii) the accuracy of the forecasts used within the optimization process, and (iii) the amount of electricity produced by RES. Such aspects are believed to gain on importance in small-scale island environments, where on the one hand electricity needs of the local water system stand as a considerable share of the total electricity consumption of the island, and where on the other, load variation between off-peak and peak periods, as well as between different seasons, is typically high.

The rest of the paper is organized as follows. Section 2 reviews related work in the field and identifies gaps. Section 3 presents the proposed peak shaving method, including the three baseline forecasting models and the optimization algorithm. A real-life case study of the proposed method in the Greek island of Tilos is presented in Section 4. Finally, Section 5 concludes the paper and summarizes some key points for future research.

2. Literature review

2.1. Optimization techniques in water supply systems

The improvement of water supply systems has been mainly supported by digital techniques and software. The purpose of such software-based tools in the scheduling and the operation of water supply systems is to minimize the use of resources, to limit water losses, and to increase energy savings during the water distribution procedure. Significant energy savings can also stem from water treatment procedures, but this section focuses on water distribution optimization solutions. Traditional hydraulic modeling tools, such as EPANET (Farina, Creaco, & Franchini, 2014), have been utilized in a great extent to analyze the behavior of distribution networks, allocating users' water demands to calculation nodes. EPANET is a modeling software package for water distribution systems which was initially developed by the US Environmental Protection Agency (Rossman, 1999). It provides functionalities of hydraulic and water distribution simulations within pressurized pipe water networks, improving the intuition of the water movement within distribution systems. With the help of such software programs, several works have been implemented focusing on the design of water supply systems to meet the daily requirement of water in many areas (Adeniran & Oyelowo, 2013; Kumar et al., 2015; Ramana & Chekka, 2018).

Except for commercial software packages, the need to improve the efficiency of the water supply system operation has led to different optimization approaches aiming to enhance pump scheduling throughout the day, by explicitly proposing the specific hours during a day that the pumps should be switched on. Efforts towards this approach were initiated with the use of genetic algorithms with the aim to minimize the pumping operation cost, by exploiting the off peak electricity tariffs, and the storage capacity in the water distribution system (Mackle, Savic, & Walters, 1995). Such heuristic and meta-heuristic methodologies have also been combined with available software, such as EPANET, and applied to real water distribution networks in order to provide water supply operational strategies towards reducing cost and consumed energy (Costa, Ramos, & De Castro, 2010). The above-mentioned studies have managed to achieve important energy savings reaching up to 10% in terms of energy consumption compared to the energy consumed before the application of the proposed plans, thus paving the way towards data-oriented solutions.

Other studies have focused on combining the pumping operation scheduling optimization problem with the water level in the storage tanks. The main idea is to manage both the pumping schedule and the trigger levels to control the water system, using different trigger levels during different periods of the day, aiming to minimize peak pumping and pumping head. The application of such a genetic algorithm that incorporates historical values and integer decision variables has achieved a 20% saving on energy costs (Kazantzis, Simpson, Kwong, & Tan, 2002). Also, the existence of specific rules concerning the water system management has been addressed, including cases where the pumping stations are controlled according to the water levels of multiple tanks, or even when both the tank levels and hour of the day must be considered in order to reduce pumping in the peak tariff period (Marchi, Simpson, & Lambert, 2017).

The heuristic methods analyzed in this section offer prosperous results in terms of operational cost savings and CO_2 emissions reduction, combining economic and environmental benefits. However, the combination of the stored water level problem with pump scheduling optimization has induced increased complexity in the developed genetic algorithms and consequently led to high computational burden (Van Zyl, Savic, & Walters, 2004). Moreover, the existence of several decision variables impose some additional limits to the convergence of the utilized heuristics. In this respect, several hybrid methods, such as modified mutation mechanisms, have attempted to address the problem.

2.2. RES forecasting

A significant number of forecasting methods have been developed over the years to forecast RES production and support decisions related with energy management, pricing, and optimization, especially for wind and solar power that comprise the most common and cost-efficient types of RES (Petropoulos et al., 2021). In the field of solar power forecasting, ML regression methods like neural networks (NNs; Ghadami et al., 2021; Korkmaz, 2021), decision-tree-based models (Hassan, Khalil, Kaseb, & Kassem, 2017), and support vector machines (Eseye, Zhang, & Zheng, 2018) have been identified as the most appropriate ones due to their ability to effectively consider multiple factors influencing PV production and account for nonlinear relationships. These factors include historical data of production and weather conditions, weather forecasts, and installation conditions, among others. Nevertheless, the quantitative comparison among different forecasting methods is challenging in practice as their accuracy may depend heavily on the quality and resolution of the historical data available, the forecasting horizon examined, and the precision of the weather forecasts provided (Sobri, Koohi-Kamali, & Rahim, 2018).

Nespoli et al. (2019) compared two of the most widely ML methods used to forecast solar power, the first exploiting only historical data and the second considering in addition to the historical observations, weather forecasts. According to the results, the first model reported more stable performance, but was often less accurate than the second on sunny days. Moreover, the accuracy of both models deteriorated on cloudy days, probably due to the inaccurate weather predictions provided to the models as input for these days. These results highlight the importance of accompanying solar power forecasting models with precise weather forecasts, such as ambient temperature, solar irradiation, and cloud coverage, and illustrate why hybrid methods and ensembles (Kourentzes, Barrow, & Crone, 2014) are widely used to tackle model, data, and parameter uncertainty (Petropoulos, Hyndman, & Bergmeir, 2018).

2.3. Load forecasting

Load forecasting is critical for effective power system operation and planning. Depending on the forecasting horizon considered, that may span from minutes to years, different types of data and models may be required for designing accurate forecasting solutions (Petropoulos et al., 2021). In operations management settings, short-term forecasts, spanning from 1 h to 168 h (one week) ahead, are the most useful ones as they support decisions related with bidding, portfolio optimization, and tariff design, as well as energy conservation techniques, such as load shifting, peak shaving, energy-storing, and load balancing (Spiliotis, Petropoulos, Kourentzes, & Assimakopoulos, 2020).

Several forecasting methods have been proposed over the years for short-term load forecasting (Kuster, Rezgui, & Mourshed, 2017; Suganthi & Samuel, 2012). A specialized state-of-the-art review for energy prediction in buildings has been conducted by Sun, Haghighat, and Fung (2020). In general, forecasting methods can be categorized into time-series, ML, and hybrid methods. Time series forecasting methods involve families of statistical models like ARIMA and exponential smoothing that identify patterns in historical load data and extrapolate them in time (Ferbar Tratar & Strmčnik, 2016). Time series methods are intuitive and fast to compute, but of limited adaptability and capability to model non-linear relationships. ML forecasting methods can effectively deal with these limitations, being also capable to efficiently incorporate information related with weather conditions, calendar effects, special days and events, and other factors that may affect demand. The most popular ML models used in the field are NNs (Li, 2020) and, most recently, deep learning (Oreshkin, Dudek, Pełka, & Turkina, 2021). Nevertheless, regression-tree-based ML models, like XGBoost, have also become popular, showing promising results in various load forecasting applications (Abbasi et al., 2019; Aguilar Madrid & Antonio, 2021; Liu, Luo, Zhao, Zhao, & Han, 2018; Wang et al., 2021), while being relatively faster to compute and easier to parameterize than NNs. Finally, hybrid forecasting methods involve the integration of time series or ML models with the objective to mitigate model uncertainty (Bozkurt, Biricik, & Taysi, 2017).

2.4. The need for a data-driven approach

Nowadays, the bulk of generated data is continuously increasing. Energy domain real time data are created by Internet of Things technologies, including smart meters for energy consumption and RES production (Saadi et al., 2020), sensor based data (Liu et al., 2020), energy efficiency investments data (Sarmas, Spiliotis, Marinakis, Koutselis, & Doukas, 2022) and grid-based assets like transformer feeders (Kong, Liu, Shen, Hu, & Ma, 2020). Also, access to open data, like weather or energy historical data, has been simplified, opening new opportunities for model development and pattern recognition approaches. Other data, which is not directly related to the energy sector, such as water pumps data, are also available and can be incorporated in the developed algorithms. All these data sources undoubtedly offer opportunities to develop a multi-scale and multi-stakeholder approach, in the form of novel analytics aiming to provide energy stakeholders with more robust and actionable insights, enhancing data-driven decision making (Marinakis, 2020; Marinakis et al., 2020). Therefore, the purpose of this study is to exploit ML models and optimization techniques in order to add value to available data related with electricity consumption, PV production, weather conditions, and shiftable loads (water pumps), proposing an integrated scheduling plan towards an automated approach for water supply systems management in the challenging environments of small scale islands.

3. Proposed method

The proposed energy management method is based on two pillars. The first pillar involves two ensembles of three baselines forecasting models, responsible for predicting the electricity produced by RES and the total electricity consumed by the system. The second pillar involves a heuristic optimization algorithm that optimally allocates the operating hours of the pumps each day with the objective to minimize predicted peaks. The above-mentioned pillars are dynamically combined in order to create an integrated scheduling plan for the water supply system that both shaves peaks and ensures water availability.

3.1. Baseline forecasting models

This section presents the three baseline ML models used in this study for forecasting electricity production from PV and consumption, including details about the training and optimization process. Note that, as it will be explained latter in this section, the final forecasts are essentially an ensemble of the forecasts produced by the baseline models. Also, mention that although each forecast variable is predicted independently, in both cases the baseline models employed share the same principles and design. Following the recent findings in the literature, both decision-tree-based models and NNs were selected to produce energy forecasts, being regarded as the most popular and accurate types of ML methods in the field (Petropoulos et al., 2021).

Decision tree models recursively split the data space according to some features (independent or explanatory variables) and fit a simple prediction model within each partition (Loh, 2011). Each leaf of the tree is paired to a specific class representing the most suitable target value. The prediction for new instances is achieved by a navigation starting from the root of the tree down to a leaf, based on the outcome of the conducted comparisons along each node of the tree (Rokach & Maimon, 2005). Although decision trees were originally developed for solving classification tasks, they also suit well in regression tasks where the dependent variable takes continuous values (Makridakis, Spiliotis, & Assimakopoulos, 2018). In this case, the loss function (forecast error) used for training the model is usually the mean squared difference between the realized values and the predicted ones (Loh, 2014). Two different implementations of regression trees where considered: the *XGBoost* tree boosting system and the *LightGBM* gradient boosting regression tree algorithm. Both implementations are very popular among the ML and forecasting community, with LightGBM being considered as the standard method of choice in most Kaggle's recent forecasting competitions (Bojer & Meldgaard, 2021).

NNs are based on a set of multiple connected nodes, typically aggregated into layers, that transmit information to each other. Each neuron receives numeric values as input and combines them using particular weights and (non-linear) activation functions. The weights, which are essentially the trainable parameters of the model, are adjusted as learning takes place so that the forecast error of the model is gradually reduced. Although various types of NNs, such as recurrent NNs (Hewamalage, Bergmeir, & Bandara, 2021), have been proposed in the literature for time series forecasting, multilayer perceptrons (MLPs) are still regarded as one of the most effective implementations of NNs, finding excellent deep learning applications in load forecasting (Oreshkin et al., 2021), among others. As a result, in this study we focus on multi-layer feed-forward NNs, carefully tuned for the particularities of the examined data set.

XGBoost (Chen & Guestrin, 2016) is an ensemble method based on decision trees that uses a gradient boosting approach to generate robust forecasts, supporting various objective functions, including regression, classification, and ranking. *XGBoost* has been utilized in order to solve several real-world scale problems, minimizing the necessary amount of resources (Ma & Yan, 2019). Similar to *DecisionTreeRegressor*, *XGBoost* involves several hyper-parameters which affect the precision of the forecasts. The most influential ones are the *learning rate*, also referred as `eta`, which is the extent of shrinkage for the feature weights making the boosting process more or less conservative, the *minimum split loss*, also referred as `gamma`, which represents the minimum loss required to make a partition on a leaf node of the tree, and the *maximum depth* of the tree, which affects the complexity of the model, with the risk of overfitting. Similar to *DecisionTreeRegressor*, a grid search was used for fine tuning the hyper-parameter values. More specifically, *learning rate* is set between (0.1, 0.6) with step 0.1, *minimum split loss* between (2, 20) with step 2, and *maximum depth* between (1, 25) with step 5.

LightGBM (Ke et al., 2017) is another novel gradient boosting decision tree ML algorithm, enhancing the state-of-the-art performance in many ML tasks in terms of efficiency and accuracy. The algorithm has been applied on various applications in the energy sector, such as wind power forecasting (Ju et al., 2019) and electric load forecasting (Park, Jung, Jung, Rho, & Hwang, 2021), among others. *LightGBM*, like the above-mentioned algorithms, involves several parameters which are crucial for its behavior. The most important ones are the *learning rate*, the *number of leaves*, the *bagging fraction*, which allows to decrease the variance in the prediction, and the *feature fraction*, which enables the random selection of a subset of features on each iteration. Once again, grid search was performed to identify the most appropriate hyper-parameters, considering values between (10, 50) with a step of 5 for number of leaves and (0.1, 0.9) with a step of 0.1 for all other hyper-parameters.

MLP is a supervised learning algorithm in the class of feed-forward NNs (Haykin, 1994), that incorporates the capability of learning non-linear data relationships. In this study we consider the *MLP Regressor* implementation in *sklearn* (Pedregosa et al., 2011) using the adam stochastic gradient-based optimizer. The architecture of the MLP includes 2 hidden layers with 64 nodes each. Several architectures have been investigated, including deep architectures, but increasing the number of layers did not improve forecasting accuracy, probably due to the relatively low number of features available and the relatively small size of the data set. The hyper-parameters of the models have been fine tuned using grid search, considering the learning rate and batch size, as presented in Table 1.

In all cases, the optimal hyper-parameter values were determined using part (20%) of the data available for training as a validation set. To make sure that the results will be robust for various periods of time, simulating the actual post-sample forecasting performance of the baseline models and avoiding possible issues related with overfitting, the validation set consisted of observations that represented different months, days, and hours of the data set. The mean absolute and squared errors were used to identify the "optimal" combinations of hyper-parameter values for each model. The hyper-parameters optimized for each model are summarized in Table 1 along with the respective search space and selected values.

The final forecasts are produced by combining the forecasts generated by each of the three baseline models. The weights for combining the baseline forecasts are defined for each series separately during the validation (hyper-parameter optimization) phase. This strategy has been followed because ensembling has long been considered an effective technique for improving forecasting accuracy, mitigating model and parameter uncertainty, and avoiding overfitting through diversification (Petropoulos et al., 2018; Spiliotis et al., 2020). The findings of recent, major forecasting competitions highlight the value of combining (Makridakis, Spiliotis, & Assimakopoulos, 2020) and support the ensembling of regression-tree-based and NN models, like the ones examined in this study (In & Jung, 2021; Nasios & Vogklis, 2022). Alternatively, a method selecting the best model per hourly interval could be implemented, but ensembling has been proven more accurate and robust for the purpose of this study.

Table 1
The search space and the selected values of the hyper-parameters for the three ML forecasting models used in the present study. The values are reported for the PV production and electricity consumption series separately.

Model	Hyper-parameter	Min value	Max value	Step	Selected	
					PV Production	Consumption
XGBoost	learning rate	0.1	0.6	0.1	0.5	0.3
	minimum split loss	2	20	2	2	4
	maximum tree depth	1	25	5	5	5
LightGBM	learning rate	0.1	0.9	0.1	30	30
	number of leaves	10	50	10	0.1	0.3
	bagging fraction	0.1	0.9	0.1	0.7	0.7
	feature fraction	0.1	0.9	0.1	0.9	0.7
MLP	learning rate	0.001	0.01	0.002	0.001	0.001
	batch size		Values Tested: 32, 64, 28		32	64

3.2. Optimization algorithm

The purpose of the algorithm is to optimally shift the water pumping stations operating hours to hourly intervals with low expected island electricity consumption, in order to shave peaks. Two modes of operation are considered for the development of the optimization algorithm, attempting to simulate both manual and automatic operation. In the first mode, to be called *"flexible"*, the operating plan of the pumping stations is unrestricted, which can be interpreted as a flexibility to start and stop the pumping stations at any hour of the day. The second mode simulates a *"constrained"* operating plan for the pumping stations, which means that the operation of a station should be continuous and it can only stop when the daily required hours are completed. In both modes of operation the optimization algorithm requires the following input:

- The number of available pumping stations (N).
- The number of required operating hours for each pumping station during a day ($PHours$).
- The hourly electricity consumption (installed power) of each pumping station ($PCons$).
- The predicted net electricity load of the island (excluding the pumping stations' consumption) for each hourly interval during a day ($TCons$).

Algorithm 1: Pump scheduling algorithm (flexible mode of operation)

Inputs : N: number of pumps
$PCons$:$\{x_1, x_2, \dots, x_N\}$, consumption per pump
$PHours$:$\{y_1, y_2, \dots, y_N\}$, operating hours per pump
$TCons$:$\{z_1, z_2, \dots, z_{24}\}$, consumption per hour interval
Output: $OperPlan[i, j]$: the operating plan; 1 if pump i is mapped to interval j; 0 otherwise

```
while PHours != 0 do
    for PHours[i] > 0 do
        utilized pump ← max(PCons);
    end
    max consumption ← PCons[utilized pump];
    for OperPlan[utilized pump, j] == 0 do
        utilized interval ← min(TCons);
    end
    OperPlan[utilized pump, utilized interval] ← 1;
    TCons[utilized interval] ← TCons[utilized interval] + max consumption;
    PHours[utilized pump] ← PHours[utilized pump] − 1;
end
```

The pseudocode of the developed optimization algorithm for the flexible mode of operation is presented in Algorithm 1. The operation scheduling of the pumps is designed targeting to shave the net load (i.e. total load minus PV-based electricity production) peaks at the island grid level. In this respect, the algorithm selects the pumping station operated at the maximum net electricity load point and it assigns the respective pump to the interval with the minimum hourly load according to the island's energy consumption forecasts, as well as the PV production forecasts. After the mapping of the selected pumping station to the selected interval has been completed, the algorithm proceeds with the necessary updates on the variables $TCons$, which describes the total consumption of the island, and $PHours$, which includes the remaining hours that each pumping station must operate. The whole process is repeated until all operating hours of every pumping station have been mapped to the optimal interval, as shown in the flowchart of the optimization algorithm, available in the appendix. Note that, in this mode of operation, the algorithm provides a global minimum concerning the achieved peak shaving.

In the second mode of operation, where the operation of the pumps is constrained, the optimization algorithm is partially altered providing a solution which may not be the optimal in some cases, but it approximates the optimal solution of the problem regarding peak shaving. Firstly, the algorithm selects the pumping station with the maximum hourly consumption, as the algorithm of the first mode does. The difference in this approach is that the algorithm selects a multi-hour interval, equal to the pumping station's daily operating hours, because of the continuous operation constraint. More specifically, the algorithm explores all possible multi-hour intervals aiming to find the hourly interval with the maximum energy consumption in each one. Finally, it maps the pumping station to the multi-hour interval which includes the minimum of these values, attempting to prevent peaks from happening. This procedure resumes until all pumping stations have been mapped to a multi-hour interval. The dynamic allocation of pump stations to hourly intervals ensures that no new peaks will be created throughout the process, because of the algorithm's property to update the net load of the selected hourly interval after allocating a new pump to it. The proposed optimization algorithm has been implemented in Python 3.0 Programming Language and it has been extensively evaluated on a case study described in Section 4.

We should note that, in order for the peaks to be identified more precisely and smoothed accordingly, net electricity load should ideally be computed by taking also into consideration both the configuration of the power grid and the respective losses. Although this information was unavailable for the case examined in the present study, it should be exploited in similar applications when accessible. Nevertheless, given that the proposed optimization method focuses on relatively small, remote islands, the effect of the losses is expected to be of secondary importance due to the short length that the distribution network has in such cases.

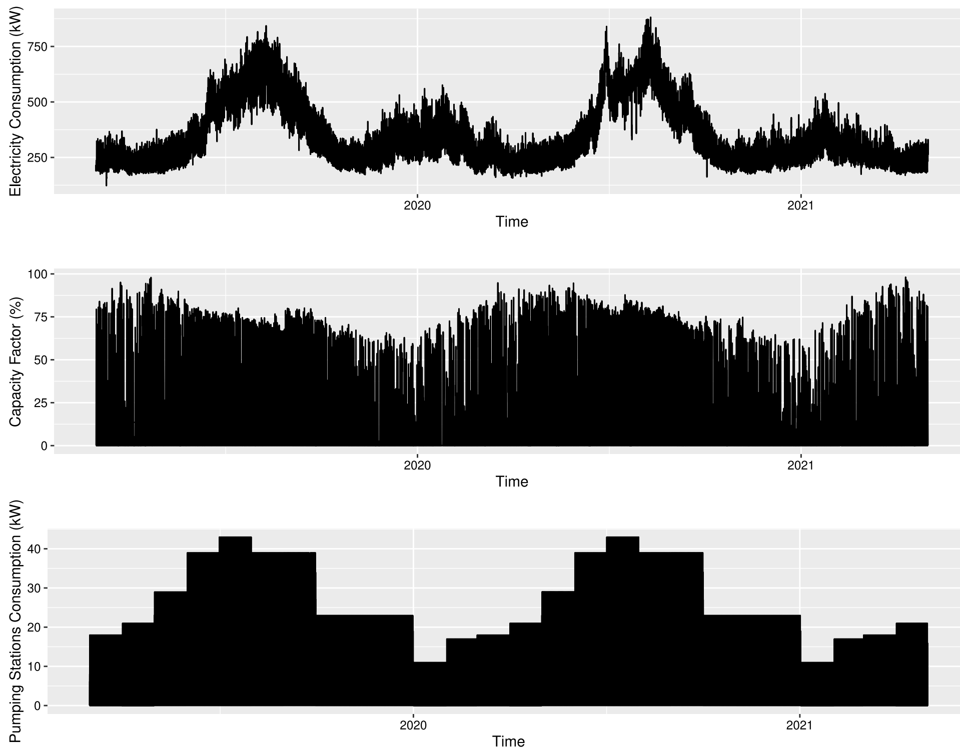

Fig. 1. Hourly time series representing the total electricity consumed (kW) on the island of Tilos, the PV capacity factor (%), and the electricity consumed (kW) by the five water pumping stations (total of the five stations).

4. Case study

4.1. Data set

In order to evaluate the potential of the proposed optimization method in terms of peak shaving, the case of Tilos is considered. Tilos is a typical small Greek island and municipality located in the Aegean Sea and belonging to the Dodecanese island chain. It stands as a remote island that has advanced considerably towards green energy transition over the last years, supported also by the implementation of the TILOS Horizon 2020 project (TILOS, 2015). In the context of the project, the first-ever, fully licensed RES-battery hybrid power station in Greece was developed, able to cover a large share of the local electricity consumption. At the same time, smart metering and demand side management aspects were also put forward, with the local water pumping stations comprising a pool of increased flexibility and sufficient response impact to that end.

In addition to the centralized hybrid power station, distributed RES (PVs) have also emerged during the recent period on the island. Thus, historical operation data from distributed PV systems were used in this study as input to the proposed optimization method and forecasting models. The empirical evaluation of similar schemes is also investigated, integrating local PV power at different scales with water pumping assets of fixed characteristics. The water pumping assets of the study include a fleet of five water pumps on the island of Tilos, monitored and controlled through a central management platform.

The data used are hourly and have a duration of about 2 years and three months (19008 h), ranging from 1 March 2019 to 30 April 2021. The data set includes the total electricity consumed on the island of Tilos, the electricity produced,[1] by the PV panels (4.8 kW installed power), and the electricity consumed by the five water pumping stations. These time series, presented in Fig. 1 will be the key input variables of the proposed optimization method.

It is worthy of mention that the electricity consumption of the water pumping stations is computed through their schedule of operation. Specifically, each pumping station operates at different hours across the day, as shown in Fig. 2. These hours are predefined and fixed within each day of the same month, but differ across the months to effectively take into account the needs of the island in terms of residential water supply and irrigation. Moreover, the installed power of the pumping stations differs (6, 10, 16, 2, and 11 kW for stations 1, 2, 3, 4, and 5, respectively), depending also on other parameters (e.g. borehole water level, available head, etc.) that together they define the volume of water transferred to local water tanks prior its distribution and final use. Therefore, in order for the proposed optimization to be meaningful and ensure adequate water supply, both on a daily and a monthly basis, it must make sure that the total daily and monthly operating hours of each pump remain equal to the ones currently determined by the operators of the stations.

As seen in Fig. 1, all series are characterized by strong yearly seasonal patterns. The total electricity consumption is higher in the summer and especially in July and August, probably due to the increased tourism activity and air-conditioning use, being significantly lower in the rest of the year. Yet, December and January do display some notable peaks. Similarly, the PV electricity production is larger in the summer, as well as in April, May, and September, being significantly lower in the winter. Moreover, as shown in Fig. 3, the series display strong daily seasonality, driven by human behavior and weather conditions. For instance, due to the daily solar radiation seasonality, PV electricity production peaks at midday and diminishes in the early morning and night hours. On the other hand, energy consumption grows after 09:00, reporting a peak at around 20:00. Interestingly, daily patterns of PV-based electricity production and island consumption differ, indicating that even large-shares of PV-based energy supply are insufficient to effectively shave consumption peaks in a natural way

[1] To facilitate comparisons in the experiments and better discuss findings, the PV capacity factor (solar power divided by the installed power, expressed as a percentage) instead of the solar power per se (measured in kW) is reported.

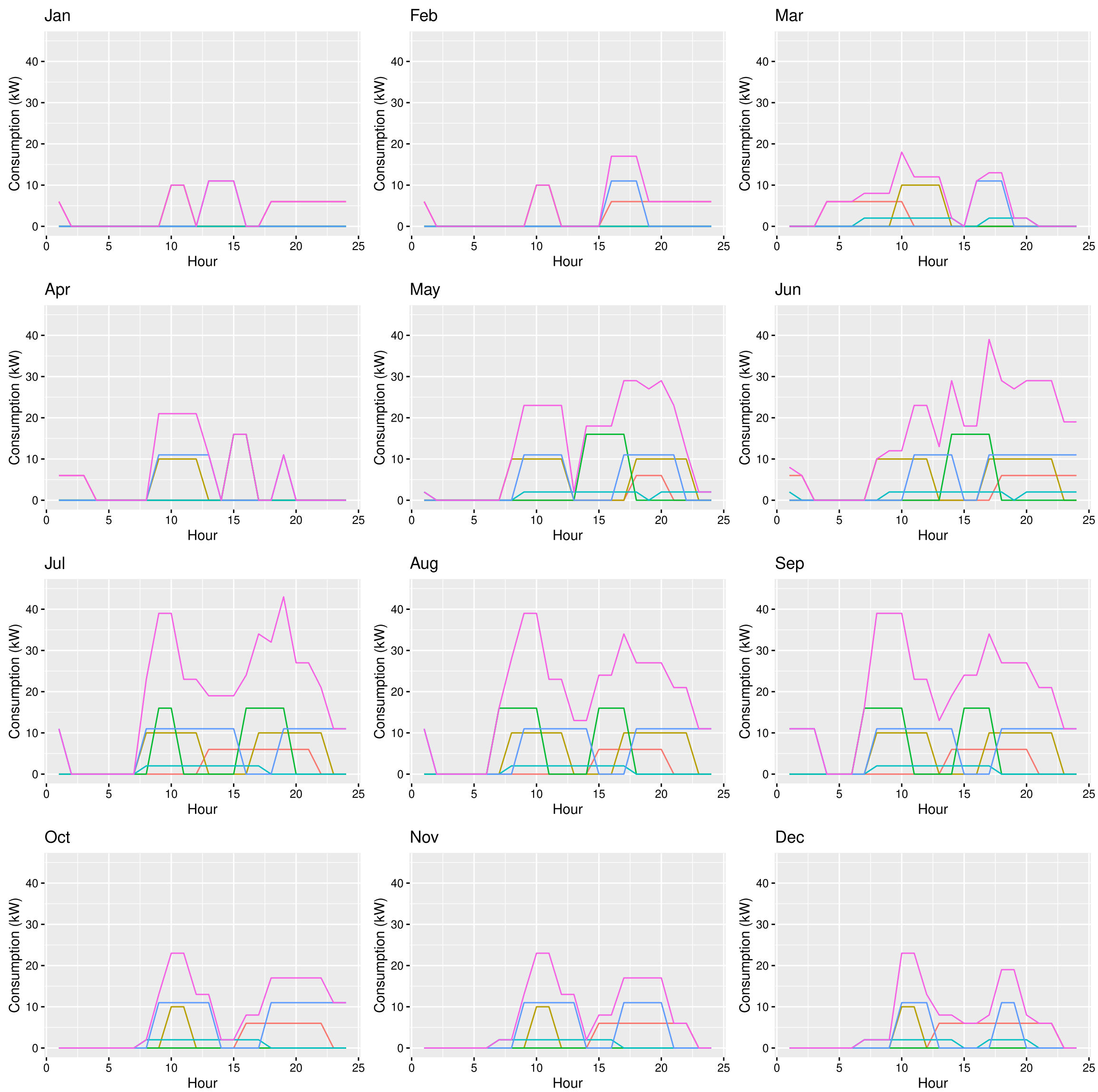

Fig. 2. Daily electricity consumption of the five pumping stations considered in this study. The daily schedule of operation changes across different months but remains the same within each month. The total electricity consumed by the stations is displayed in purple. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(real-time self-consumption) unless proper load shifting actions are performed. Nevertheless, water pumping stations are mostly operated at midday and afternoon hours, meaning that energy managers could shave peaks by suitably adjusting the current operating hours of the pumping stations. The mismatching between the total electricity consumption and PV production (Pearson's correlation coefficient of 0.1), as well as the matching between the electricity consumed at island and water pumping station levels (Pearson's correlation coefficient of 0.5) further motivate this study and illustrate the potential value of the proposed optimization approach, especially in small-scale environments where the sensitivity of such mismatches is relatively strong.

In addition to the three series presented in Fig. 3, the data set includes hourly weather forecasts that will be exploited to accurately predict solar power. Specifically, weather forecasts refer to solar radiation (measured in W/m^2), temperature (measured in °C), cloud coverage (ranging from 0 to 8, with the former value suggesting no coverage and the latter value complete coverage), and wind speed (measured in m/s) predictions made on a weekly basis. The distributions of these variables are visualized in the histograms of Fig. 4.

4.2. Experimental design

In order to simulate the performance of the proposed method as realistically as possible, a rolling origin fashion-based approach is employed, considering an overall evaluation period of 8760 h (1 year). This allows us to assess its benefits in the long term, while taking into consideration calendar and weather factors that may impact its performance across the year. According to this setup, the first 10248 observations available are used to train the proposed forecasting models, as described in Section 3.1. Then, the total electricity consumption of the island and the solar power for the following 168 h (1 week) are predicted. Using these forecasts as an input, the algorithm described in Section 3.2 is applied in order to define an "optimal" schedule of operation for the water pumping stations of the island. Then, based on the realized electricity consumption and PV production reported for the week that was forecast earlier, the impact of the proposed plans are measured using the following key performance indicators (KPIs):

1. SD_{day}: Average standard deviation of electricity consumption, measured on a daily basis.

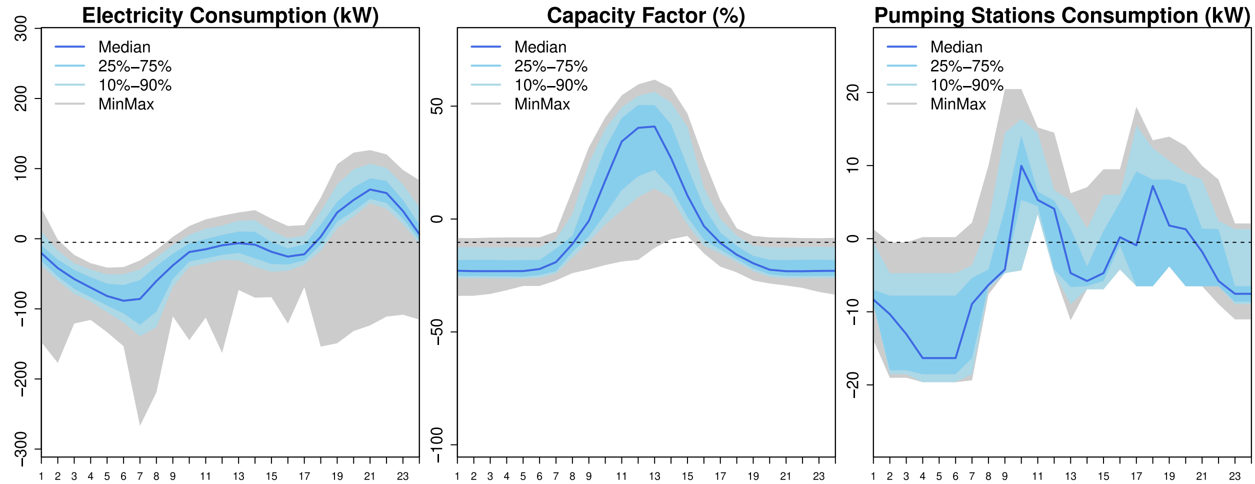

Fig. 3. Distribution of seasonal indices (computed using an additive decomposition with moving averages; Spiliotis et al., 2020) for the total electricity consumption (left), PV capacity factor (middle), and water pumping stations consumption (right). Low variance of indices around the seasonal profile (blue line) suggests time series with strong daily seasonality (observations overlap every 24 h). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

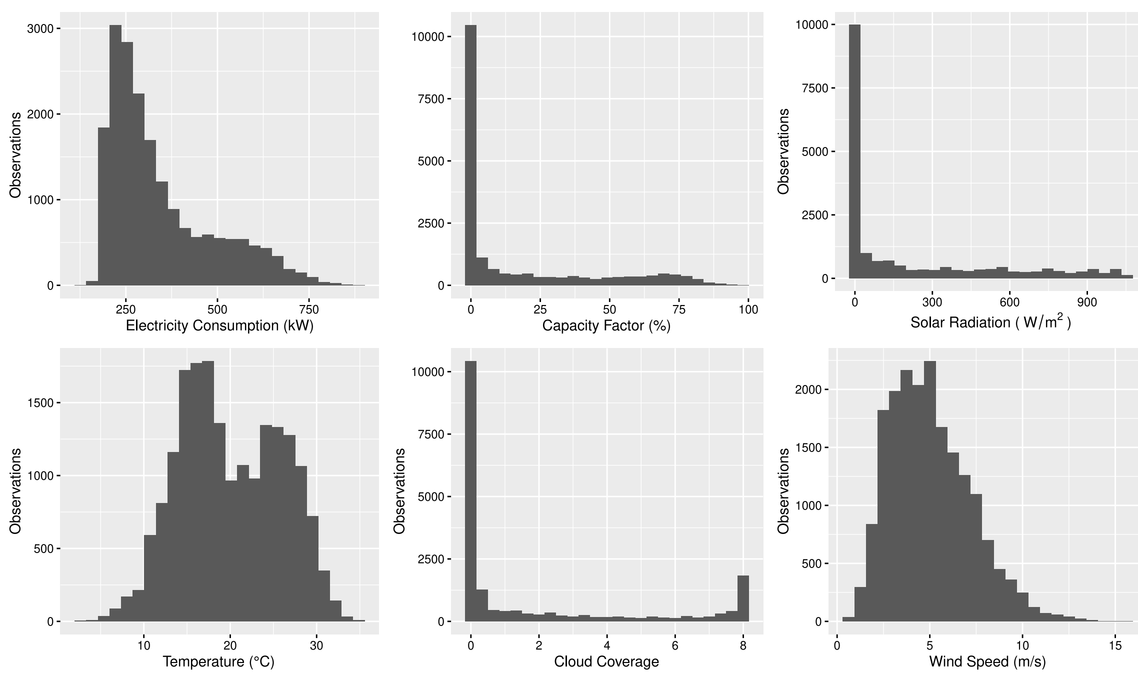

Fig. 4. Distributions (histograms) of the variables considered by the proposed optimization method in the examined case-study (electricity consumption, PV capacity factor, and weather forecasts).

2. SD_{week}: Average standard deviation of electricity consumption, measured on a weekly basis.
3. $Max - Min_{day}$: Average difference between maximum and minimum electricity consumption, measured on a daily basis.
4. $Max - Min_{week}$: Average difference between maximum and minimum electricity consumption, measured on a weekly basis.
5. $Max - Mean_{day}$: Average difference between maximum and mean electricity consumption, measured on a daily basis.
6. $Max - Mean_{week}$: Average difference between maximum and mean electricity consumption, measured on a weekly basis.

The aforementioned KPIs are inspired by the study of Feng, Niu, Wang, Zhou, and Cheng (2019), who proposed the standard deviation and the difference between maximum and minimum value (peak–valley difference) for the evaluation of a mixed integer linear programming model for a peak shaving problem involving thermal power plants. Moreover, these metrics have been exploited either as KPIs or as the objective function in a variety of similar peak shaving problems, such as the peak shaving operation of cascade hydro-power plants (Liao et al., 2021) and of hydro-thermal-nuclear plants in an environment of multiple power grids (Feng, Niu, Cheng, & Zhou, 2017), emerging as the most suitable indicators for evaluating the peak shaving performance of the proposed optimization algorithm. To enable direct comparisons, the KPIs are also computed for the realized energy consumption, i.e., the “business as usual” (BaU) mode of operation where no optimization takes place and the water pumps operate according to the usual schedule.

After completing the first evaluation round, the forecast origin is moved forward by 168 h, using the first 10416 observations available to retrain the proposed forecasting models, and reapplying the optimization algorithm to measure its performance for the second week of the test set. This process is repeated till there are no observations left. As a result, a total of 52 evaluation periods are available, that sufficiently represent the performance of the optimization method.

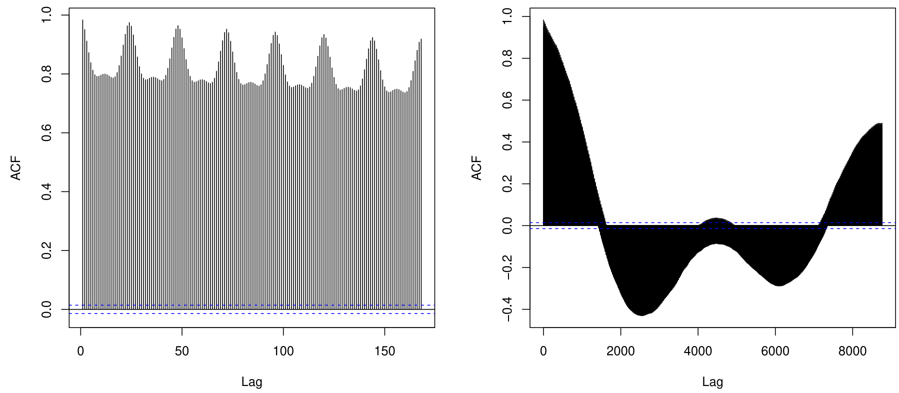

Fig. 5. Autocorrelation function of the total electricity consumption computed across the week (168 h) and the year (8760 h).

Note that the updating frequency of the proposed schedule of operation was carefully selected after taking into consideration some practical constraints. For example, the weather forecasts are currently provided to the energy management system (EMS) through a web service on a weekly basis. Thus, recalculating solar power forecasts on a daily basis becomes impossible. Moreover, although most EMS can automatically adjust the operating hours of the pumping stations, energy managers may still have to approve any changes made, an action which is not always feasible to perform on a regular basis. Nevertheless, the proposed method can be easily adjusted to allow for more frequent updates compared to those examined in this study, a practice that could allow for more accurate energy forecasts and, therefore, better optimization.

In the conducted experiments two modes for implementing the proposed optimization method are considered. In the first mode of operation, to be called *"flexible"*, the operation of the pumps is completely flexible and the pumping stations can be started and stopped at any hour of the day. In the second mode of operation, to be called *"constrained"*, the operation of the pumps is constrained and, after a station starts, it cannot be stopped till its daily required operating hours have elapsed. In this regard, the first mode simulates fully automated systems that remotely control water pumps, while the second mode simulates systems where water pumps are manually controlled by energy managers. As a result, the differences reported between these two modes can effectively demonstrate the potential benefits of automated systems versus non-automated ones.

4.3. Forecasting models and accuracy

As explained in Section 3, the optimization algorithm builds on forecasts that represent future electricity consumption and PV production. In general, higher forecasting accuracy is expected to result in more effective energy management. In this case, the forecasts required by the algorithm refer to the total electricity consumption of the island and the solar power. In both cases, the forecasts are produced using an ensemble of ML models, as described in Section 3.1. Nevertheless, given the particularities and the nature of each series, different features are used as input per case to facilitate training and enhance forecasting accuracy.

Electricity consumption is characterized by strong seasonal patterns, observed both at a daily and an annual level. This becomes evident by observing Figs. 1 and 3, as well as Fig. 5 that presents the autocorrelation function of the respective series across the week (168 h) and the year (8760 h). Auto-regression, i.e., using past electricity consumption observations as features to forecast future ones, is a promising forecasting approach, especially if categorical variables like month, week, weekday, and hour of the day are included among the features to facilitate pattern recognition. Therefore, the aforementioned features (lag 168 and calendar variables) are the only regressors considered by the baseline ML models to forecast electricity consumption.

Solar power is stochastic in nature and mostly driven by weather conditions. Therefore, in contrast to the previous models, past observations are not considered as features and predictions are based on the weather forecasts available in the EMS. Fig. 6 provides comparisons between the solar power and the weather forecasts used for its prediction. As expected, solar radiation is strongly related with PV production, being a critical predictor. Temperature and wind speed are also positively related with solar power, but to a much weaker extent. Finally, although higher cloud coverage typically leads to less energy being produced, its explanatory power is limited, probably due to the uncertainty the forecasts of this particular variable involve. Nevertheless, in order to help the baseline forecasting models capture calendar effects and daily seasonality, we do include the month, week, and hour of the day (categorical variables) among its features.

The accuracy of the proposed ensembles is evaluated by computing the root mean squared error (RMSE) and the mean absolute error (MAE) of the respective forecasts across the evaluation period considered, as well as the Pearson's correlation coefficient between the forecasts and the realized values, as follows:

$$RMSE = \sqrt{\frac{1}{8760}\sum_{t=1}^{8760}(y_t - f_t)^2},$$

$$MAE = \frac{1}{8760}\sum_{t=1}^{8760}|y_t - f_t|,$$

$$r_{y,f} = \frac{\sum_{t=1}^{8760}(y_t-\bar{y})(f_t-\bar{f})}{\sqrt{\sum_{t=1}^{8760}(y_t-\bar{y})^2}\sqrt{\sum_{t=1}^{8760}(f_t-\bar{f})^2}},$$

where y_t is the actual future value of the examined time series at hour t of the evaluation period, f_t the forecast of the model used for producing the forecasts, while $\bar{y}$ and $\bar{f}$ the average of the actual and forecast values, respectively. The choice of the selected performance measures can be justified as follows: Squared errors, like RMSE, are optimized for the mean (Kolassa, 2016), evaluating forecasting models based on how skillful they are in estimating the average electricity produced/consumed, while also penalizing more larger errors that typically occur during peak hours. On the other hand, absolute errors, like MAE, are optimized for the median (Schwertman, Gilks, & Cameron, 1990), providing evidence about how accurate the developed models are in forecasting electricity production/consumption values that appear more often, while also being more robust to extremely large errors and focusing on non-peak hours. Finally, the correlation coefficient indicates whether the forecasts are sufficiently linearly correlated with the actual future values or not, i.e. if the developed models are capable

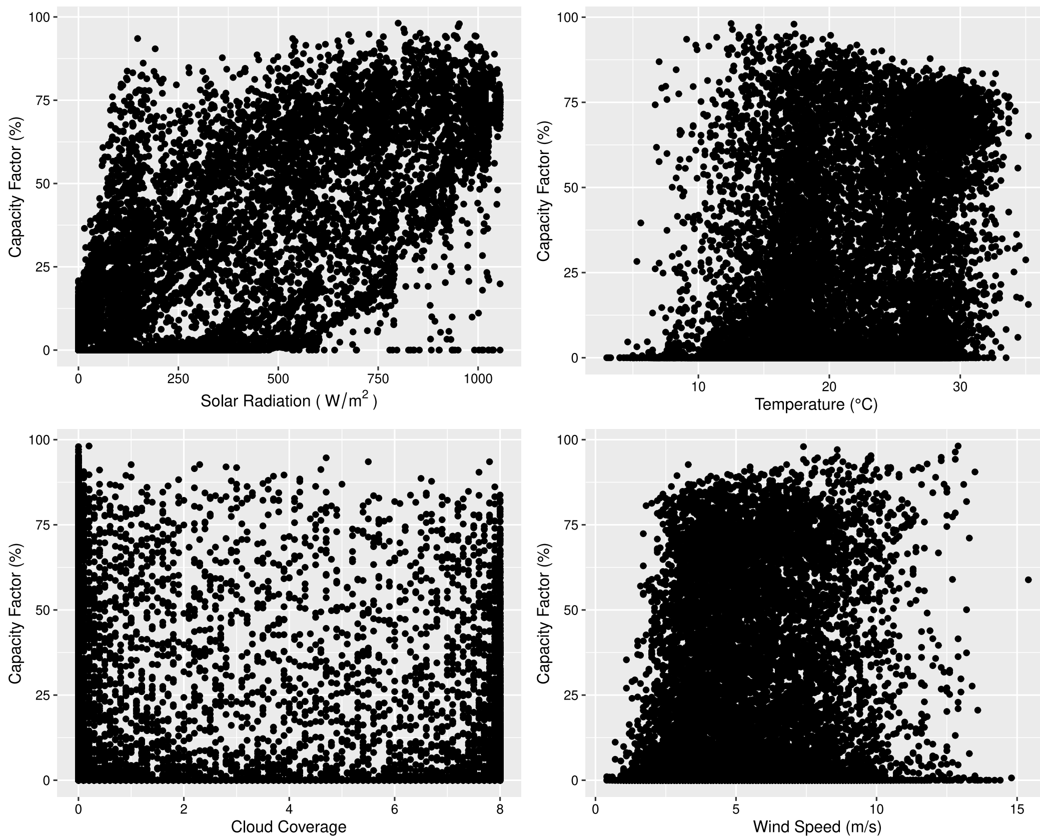

Fig. 6. PV capacity factor (%) compared with solar radiation (W/m^2), temperature (°C), cloud coverage, and wind speed (m/s). The Pearson's correlation coefficients are 0.82, 0.30, −0.11, and 0.22, respectively.

Table 2
Forecasting performance (accuracy) of the ensemble of ML models utilized in the case study.

Measure	Electricity consumption	Solar power
$RMSE$	32.58	0.34
MAE	22.54	0.14
$r_{y,f}$	0.97	0.96

of predicting the variation in the target series. Although no accuracy measure is perfect, having both advantages and drawbacks (Koutsandreas, Spiliotis, Petropoulos, & Assimakopoulos, 2021), we believe that this set of measures can effectively summarize the overall performance of the proposed models across the most critical dimensions of the examined forecasting task.

The results are summarized in Table 2. As seen, both ensembles are adequately accurate given the forecasting horizon of one week, capturing the daily patterns of the key variables considered by the proposed optimization method. Moreover, as shown in Fig. 7, the ensembles manage to effectively capture the seasonality, trends, and weather-related variations of the series being forecast, both in summer and winter periods.

4.4. Optimization results

Having obtained the forecasts for each week the simulation takes place, the proposed optimization algorithm is applied to properly adjust the schedule the pumps operate and shave peaks. Fig. 8 provides two indicative examples of the optimization process, presenting electricity consumption in a summer and a winter week of the simulation under the BaU mode of operation, as well as the flexible and the constrained modes. We observe that both optimization modes result in similar gains in terms of variation, effectively shaving the peaks and increasing consumption at hours of lower intensity. Moreover, as expected, the impact of peak shaving is more evident in the summer week since both the PV-based electricity production and the amount of load that can be shifted are larger compared to the winter week.

The daily changes applied on the original operating hours of the pumps are summarized in Fig. 9 for each optimization mode of operation separately. As seen, in both cases the algorithm suggests stopping the operation of the pumps from 08:00 to 14:00 and from 18:00 to 23:00. This is because in these time intervals the expected consumption is significant while at the same time the electricity produced by the PV panels is inadequate to sufficiently cover the demand. As a result, the algorithm suggests that the pumps are operated either in the early morning hours (01:00 to 07:00), where electricity consumption is at its minimum level, or in the afternoon (15:00 to 17:00), where solar power is still notable.

The performance of the proposed optimization method across the complete simulation period is summarized in Table 3 where the KPIs introduced in Section 4.2 are used for its evaluation. We observe that, under the flexible mode of operation, the daily and weekly deviation of the consumption is reduced by about 20% and 17%, respectively. The results are slightly worse under the constrained mode, dropping to about 19% and 16%, respectively. Similarly, due to the load shifting actions, the average difference between the maximum and the minimum electricity consumption reported for the flexible mode at a daily and a weekly basis is reduced by more than 17% and 12%, respectively. Given that the installed power of the water pumping stations (45 kW) accounts for just 13% and 5% of the average and maximum electricity consumption reported for the simulated period, we conclude that the proposed method shows a lot of potential and that its utilization can result in significant improvements in terms of stability, especially when loads of energy intensive systems can be flexibly shifted.

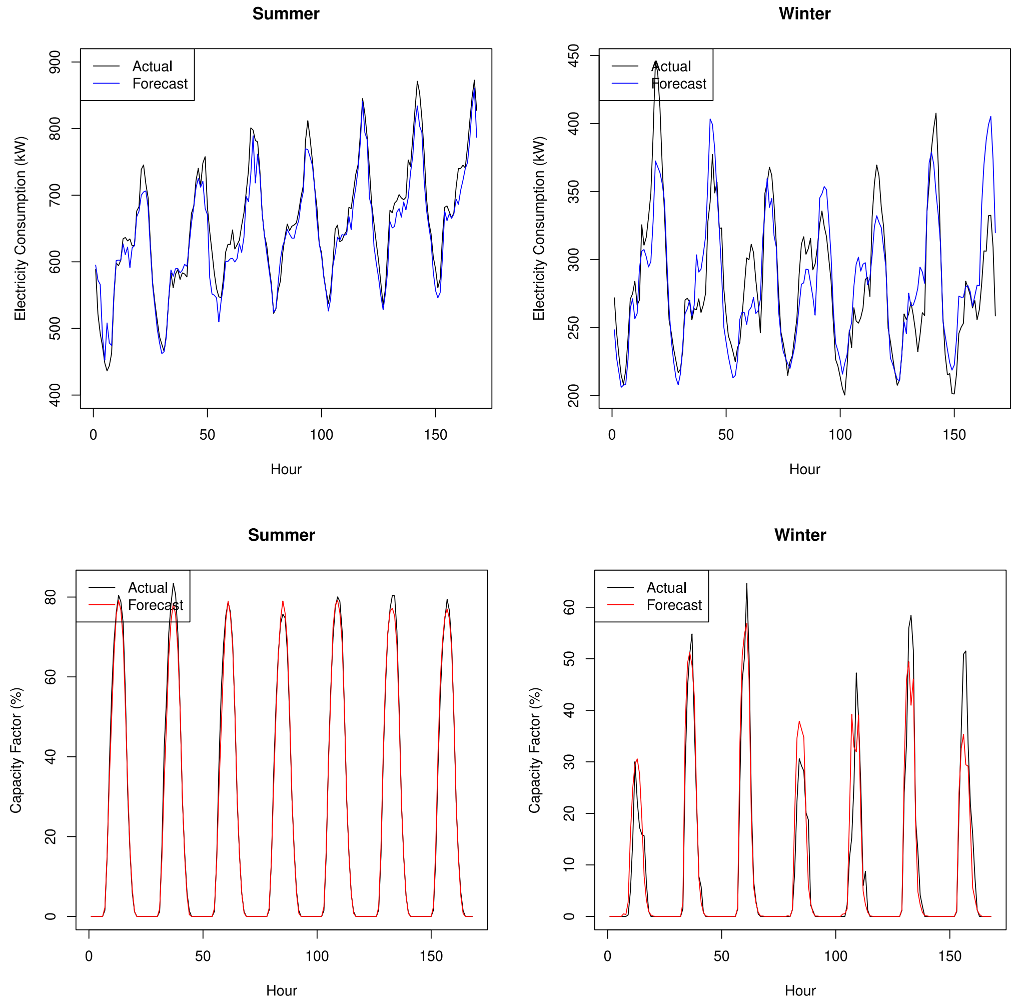

Fig. 7. Examples illustrating how the electricity consumption (top) and solar power (bottom) forecasting models perform. The examples refer to two randomly selected summer (2020-07-31 to 2020-08-06) and winter (2020-12-04 to 2020-12-10) weeks of the evaluation period.

Table 3
Performance of the proposed method in terms of peak shaving. Various KPIs are used to evaluate the daily and weekly deviation of the electricity consumption of Tilos when no loads are shifted (BaU), flexible load shifting is allowed, and constrained load shifting is performed. The percentage improvements of the two load shifting optimization modes over the BaU mode of operation are also provided.

KPI	BaU	Flexible	Constrained	Flexible	Constrained
	Absolute values			Percentage improvements (%)	
SD_{day}	51.58	41.23	41.81	20.07	18.94
SD_{week}	54.93	45.73	46.19	16.75	15.91
$Max - Min_{day}$	175.01	143.79	147.74	17.84	15.58
$Max - Min_{week}$	242.12	212.90	216.66	12.07	10.52
$Max - Mean_{day}$	98.99	87.23	87.27	11.88	11.84
$Max - Mean_{week}$	142.02	130.40	130.01	8.18	8.46

Table 4
Performance of the proposed method in terms of peak shaving (SD_{day}) when PV electricity production is increased by a factor of 10 and 40. To facilitate comparisons, the improvements of the two load shifting modes of operation over the BaU mode are provided as percentages.

KPI	Flexible	Constrained
	Percentage improvements (%)	
Original scale	20.07	18.94
Scale up (×10)	16.68	15.87
Scale up (×40)	11.96	11.34

Given that the proposed peak shaving method is partially affected by the amount of electricity produced by RES, being relatively small in this case compared to the electricity consumed, both by the complete system and the water pumping stations, we extend the analysis by artificially scaling up the installed power of the existing PV system by a factor[2] of 10 and 40. After scaling up the historical PV production data, we rerun the complete experiment and recalculate the KPIs introduced above to assess the impact of the amount of electricity produced on realized peak shavings. The results are presented in Table 4.

It can be seen that the proposed method has always a positive effect on the daily deviation of the electricity consumption, with the improvements ranging from about 12% (scaling factor of 40) to 20% (scaling factor of 1, i.e. original scale). Moreover, as expected, the constrained mode of operation is slightly less effective when compared to the flexible one, resulting in about 1%–2% less improvement. Interestingly, when scaling takes place, the improvements decrease in a damped, non-linear fashion. This is because, as discussed earlier in this section and shown in Fig. 8, there is a notable mismatch between the peak hours of consumption and PV production. As a result, when PV production is increased, consumption decreases mostly at hours where the demand is already relatively low and that would be eligible for load shifting.

[2] The factor of 10 was selected so that the electricity produced is of the same scale to the load being shifted. The factor of 40 provides a scenario where the electricity produced is greater than the load being shifted.

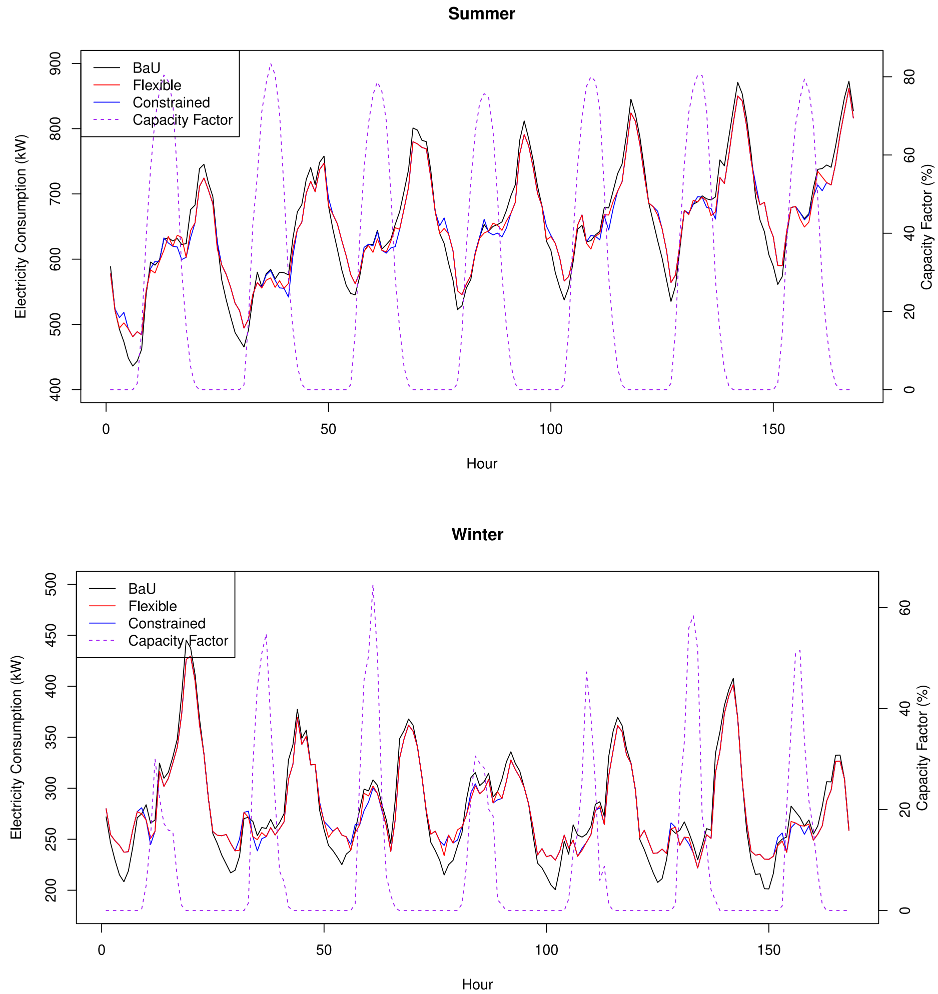

Fig. 8. Examples illustrating how the total electricity consumption of the island is adjusted when the flexible and the constrained optimization modes of operation are considered for shaving peaks. The examples refer to two randomly selected summer (2020-07-31 to 2020-08-06) and winter (2020-12-04 to 2020-12-10) weeks of the evaluation period. Solar power is also presented to facilitate comparisons.

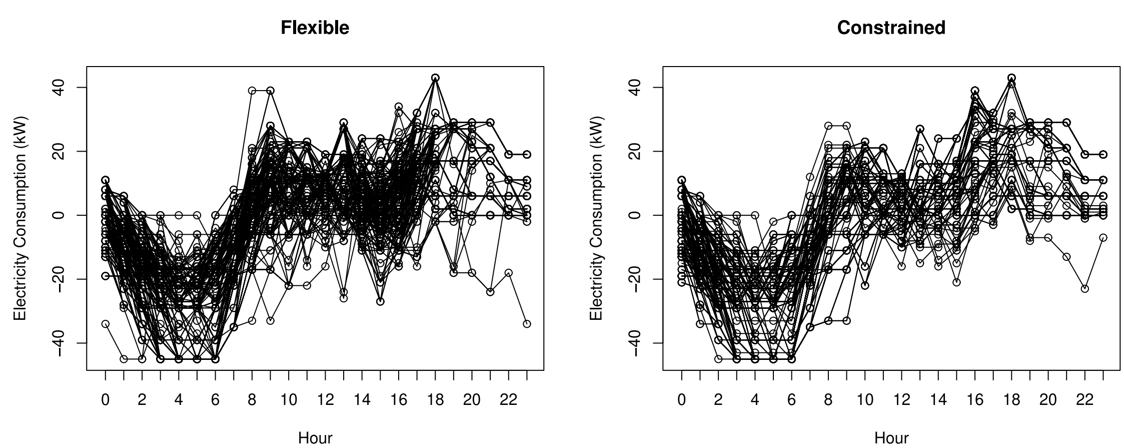

Fig. 9. Load shifting performed under the flexible and the constrained optimization modes of operation. Each line represents the daily differences reported between the BaU mode and the optimized modes (flexible or constrained). Positive values indicate hours where the algorithm has suggested against the operation of the water pumping stations, while negative values indicate hours where the algorithm has suggested in favor of the operation of the water pumping stations.

Therefore, it is evident that the amount of electricity produced and its distribution across the day affects to some extent the performance of the proposed method and that larger RES production does not necessarily guarantee better performance in terms of peak shaving. This effect is better visualized in Fig. 10 where the installed power of the existing PV system is artificially scaled up by a factor from 1 to 40 with a step of 5 and the differences computed in terms of SD_{day} between the BAU and flexible mode of operation are reported, both in absolute values and as percentages. As seen, although the proposed method improves the selected KPI by more than 8 kWh (slightly larger than the average annual

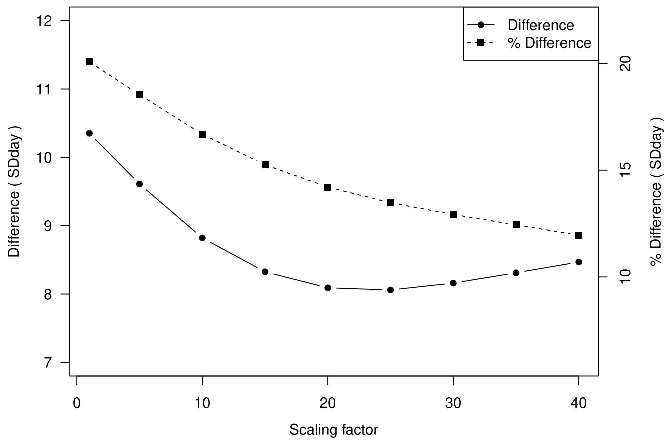

Fig. 10. Performance of the proposed method (flexible mode of operation) in terms of peak shaving (SD_{day}) when PV electricity production is increased by a factor of 1 to 40. The improvements over the BaU mode are provided both in absolute values and as percentages.

Table 5
Summary of the causal linear regression model used to relate the gains achieved by the proposed method in terms of electricity consumption stability (KPI SD_{day}) with the electricity consumption forecast error (e_c), the PV electricity production forecast error (e_p), and the amount of load that can be shifted (SL).

Coefficient	Value	Standard error	t value	Significance
Scale up (×1) – Original data				
$Intercept$	3.071	0.581	5.285	*
e_p	−2.41	1.842	−1.310	
e_c	−0.073	0.012	−5.862	*
SL	0.036	0.001	25.532	*
Scale up (×10)				
$Intercept$	2.054	0.612	3.356	*
e_p	−0.345	0.194	−1.779	*
e_c	−0.055	0.013	−4.164	*
SL	0.033	0.001	22.200	*
Scale up (×40)				
$Intercept$	3.756	0.445	8.438	*
e_p	−0.231	0.035	−6.536	*
e_c	−0.045	0.010	−4.651	*
SL	0.027	0.001	25.270	*

*Coefficients with a significance higher than 95% are marked with (*).

consumption of the water pumps), the percentage improvements shrink as the installed power increases. Moreover, after the scaling factor reaches a value of 20 (about 25% of the average annual consumption), the absolute improvements are stabilized around 13%. Drawing from the above, remote islands like Tilos should carefully define the scale of their RES production based on the profile of the energy demand and the amount of the load that can be shifted. Although defining the RES increase that would be profitable in such settings is a challenging task, being subject to the expected return on the investment among other factors, for the case of Tilos we find that the optimal scaling factor of PV due to peak shaving is linked with the average annual consumption of the water pumps and that the existing installed power is sufficient for optimally allocating the load of the water pumps.

To explicitly evaluate the impact of forecasting accuracy on the performance of the proposed optimization method, the relationship between the daily gains of the proposed approach in terms of electricity consumption stability ($SDgains_{day}$) and the respective daily MAE reported for the electricity consumption (e_c) and PV production (e_p) forecasts produced is investigated. Moreover, since the amount of shiftable loads (SL) is expected to affect these gains, the causal model is structured as follows:

$$S\hat{Dgains}_{day,i} = a_0 + a_1 \times e_{c,i} + a_2 \times e_{p,i} + a_3 \times SL_i,$$

where $S\hat{Dgains}_{day,i}$ are the expected gains in terms of stability at day i and $a_0 \dots a_3$ the coefficients of the estimated linear regression model. The values of these coefficients and their significance is summarized in Table 5 for the case of the flexible mode of operation, considering also a scaling-up factor of 1 (original data), 10, and 40 for the electricity produced, similarly to the analysis conducted earlier. As seen, with the exception of the case where no scaling in performed, all the explanatory variables used are statistically significant for estimating stability gains. Moreover, simulation results indicate that higher gains are possible when larger amounts of loads can be shifted and lower forecast errors are realized. Interestingly, when PV production is significant, producing accurate solar power forecasts is more important for maximizing gains than accurately forecasting consumption, a result that can be attributed to the important role that PV electricity production forecasts play in the optimization process.

5. Conclusions

In this study, an integrated method for smart energy management was introduced with the objective to smooth electricity consumption in remote island power systems. The innovative method was based on two pillars: the development of an ensemble of ML models, used to accurately forecast RES production and electricity consumption, and the design of a scheduling algorithm that optimally shifts the operating hours of the water pumping stations towards intervals of low expected load. Our results suggest that it is possible to significantly shave peaks while ensuring water availability and fulfilling restrictions related with the operation of the water supply system.

The developed forecasting models were fast to compute, easy to implement, and exploited a small number of input variables, including some auto-regression features for load forecasting and weather predictions for RES production forecasting. The models managed to effectively capture the daily and monthly patterns of the forecast variables and provided satisfying results in terms of accuracy. The proposed optimization algorithm was then applied to properly schedule the pumping stations' operating plan, using as input the forecasts produced by the models for each week, as well as the operation profiles of the pumping stations. The algorithm was designed to support both flexible and constrained modes of operation.

The proposed method was evaluated through a simulation that covered a full year of operation, resulting in a reduction on the daily and weekly deviation of the island's consumption higher than 15% in both modes. The proposed daily operating plan of the pumping stations involved early morning hours, where the consumption is typically relatively low, and afternoon hours, because of the energy production stemming from the photovoltaic panels. In addition, the potential gains of the proposed approach are strongly connected with the amount of load that can be shifted each day and the accuracy of the forecasts used, especially the PV electricity production ones. Moreover, results indicate that the amount of electricity produced, as well as its matching with the electricity consumed, can affect the potential of the proposed method and that higher electricity production does not always guarantee better performance in terms of peak shaving.

A future step for the improvement of the proposed method is the development of a user-friendly interface, where energy managers will be able to exploit the benefits of the developed algorithms, simulating different modes of operation. Another avenue for future research is to expand the optimization algorithm to support systems that involve energy storage or other types of RES, such as wind, biomass, and geothermal plants. Finally, different ensembling strategies could be investigated to further improve forecasting accuracy, considering also other variants of ML baseline models.

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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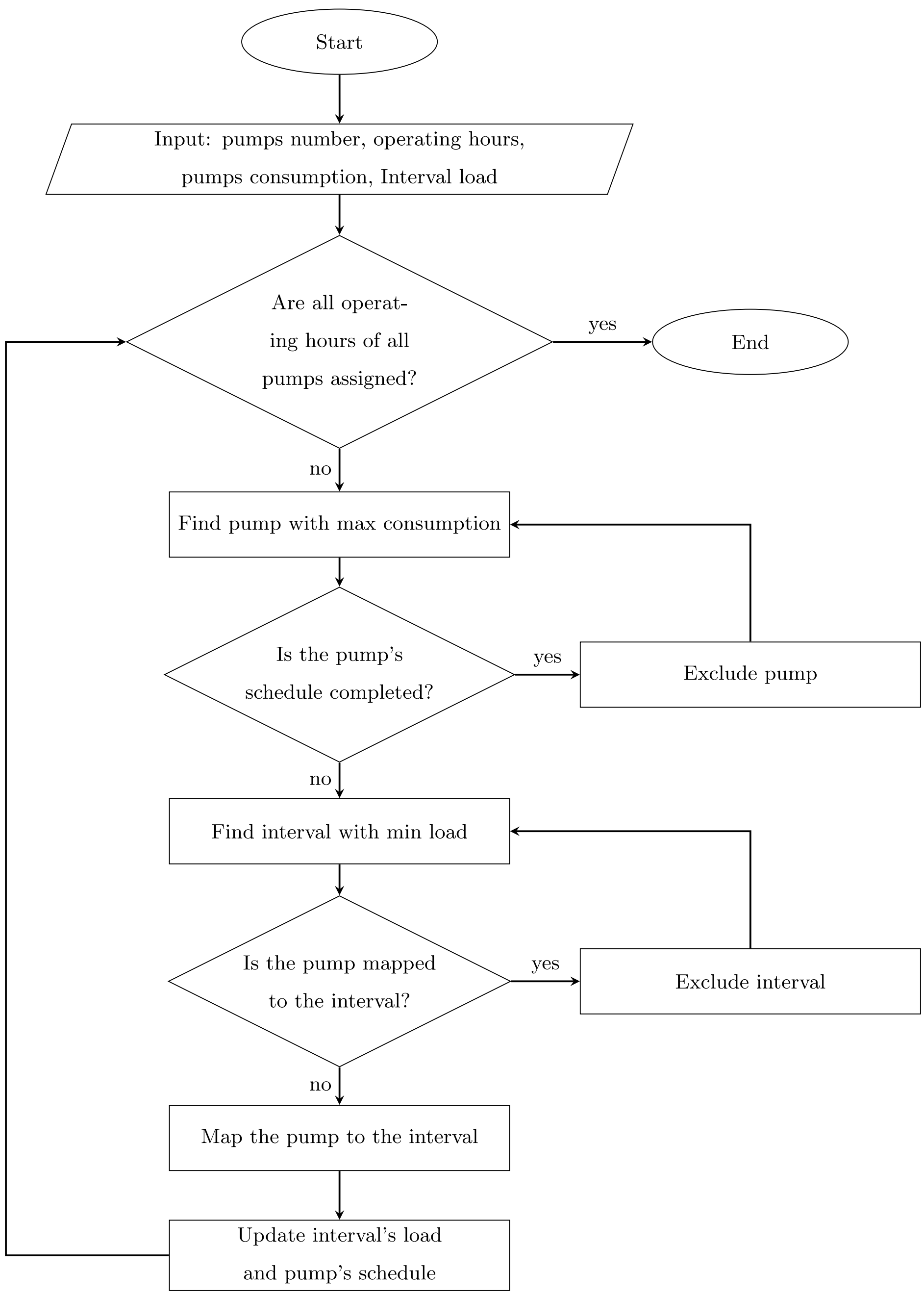
Appendix. Optimization algorithm



Flowchart of the optimization algorithm used to schedule the operating hours of the pumps (flexible mode of operation).

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