A Learning Powered Bi-Level Approach for Dynamic Electricity Pricing

Patrizia Beraldi[a], Luigi Gallo and Alessandra Rende
Department of Mechanical, Energy and Management Engineering, University of Calabria, Italy

Keywords: Bi-Level Optimization, Electricity Tariffs, Solar Production, Forecasting, Machine Learning Techniques.

Abstract: This paper presents a comprehensive approach to electricity tariff determination by integrating advanced Artificial Intelligence (AI) techniques with Bi-Level (BL) optimization. More specifically, AI techniques are used to obtain accurate forecasts of photovoltaic panel generation, which are then used as input parameters for a deterministic BL problem that models the interaction between a power supplier and a residential prosumer.
To handle the high complexity of the BL formulations, the model is first reformulated into a single-level structure, and then linearized using an approach based on the application of the dual reformulation. An intensive experimental phase is carried out on a real case study to test the effectiveness of the proposed methodology and to quantify the impact of the forecast techniques on the supplier strategy.

1 INTRODUCTION

Climate change and environmental degradation pose a severe threat to Europe and the rest of the world. In response to these challenges, the European Climate Law, effective since 29 July 2021, has established the intermediate target of reducing net greenhouse gas emissions by at least 55% by the year 2030, compared to levels recorded in 1990. Furthermore, this legislation has set the ambitious goal of attaining a climate neutral European Union by 2050. In the energy transition, end-users are acknowledged as key stakeholders. Nowadays, a growing number of consumers are evolving into prosumers, i.e. consumers that also produce energy, primarily from renewable energy sources (RES), as, for example, Photovoltaic (PV) panels. Additionally, prosumers often possess a battery energy storage (BES) device to compensate for the non-programmability of green energy production, which is by nature intermittent and unpredictable. Indeed, prosumers can accumulate self-produced energy and use it later when needed, and purchase electricity during off-peak hours when the prices are lower, thus reducing the electricity bill. In addition, the recent integration of advanced communications, metering, and control automation provides prosumers with the technical support to optimize the load management, exploiting the flexibility of controllable loads. Many modern appliances are, indeed, deemed for control and they can be properly scheduled during hours when electricity prices are lower or when self-produced energy is available, leading to significant cost savings. Proactive prosumers are often referred to as prosumagers, as they are called to optimize the management of their home energy systems in response to the market signals. Prosumers can act individually or collectively, as a single entity, as, for example, a local energy community coordinated by aggregator acting as intermediary with the market. In this paper, we study the interaction between an aggregator and a homogeneous group of residential prosumagers, comparable in terms of location, consumption patterns, flexibility and behaviour. A similar interaction can also be envisaged with a retailer, although the ultimate goal of aggregators and retailers may be different, as the former are designed to be non-profit organisations. Nonetheless, both entities aim to maximize their net profit, which, in the case of the aggregator, could potentially be reinvested in the community, for example, incentivising future investments in RES. In this paper, we focus on the electricity pricing problem analyzed from the perspective of an aggregator. In the text, the terms aggregator and retailer are used interchangeably. Specifically, we focus on a dynamic pricing scheme with rates that vary over time. Time-of-use (ToU), critical-peak pricing (CPP) and real-time pricing (RTP) are commonly used time-based pricing structures. We consider a RTP scheme, where the aggregator dynamically determines the selling prices offered to the clients for each period of a planning horizon. Such a pricing scheme is expected

[a] https://orcid.org/0000-0002-1672-4033

Beraldi, P., Gallo, L. and Rende, A.
A Learning Powered Bi-Level Approach for Dynamic Electricity Pricing.
DOI: 10.5220/0012465700003639

In *Proceedings of the 13th International Conference on Operations Research and Enterprise Systems (ICORES 2024)*, pages 390-397
ISBN: 978-989-758-681-1; ISSN: 2184-4372

to become a common practice in smart grids as it represents a mean to incentive price-based demand-response programs. Prosumers can, indeed, be motivated to change their habitual consumption patterns in response to economic signals, thereby favouring the transition from the conventional “supply follows load” paradigm to the “load follows supply” one in the long run. Due to the increasing relevance, the electricity pricing problem has been the subject of intensive research in recent years. The problem involves two different players tied by a hierarchical relation. The retailer/aggregator plays the role of leader, deciding first, whereas the prosumer the role of follower. To account for such a relation, we formulate the problem by the Bi-Level (BL) paradigm (Colson et al., 2007). Specifically, the leader solves the Upper Level (UL) problem aimed at defining the electricity rates and the procurement plan that bears the maximum profit. In taking the best decision, he conjectures the possible reaction of the follower to the offered rates as this affects the objective function. Indeed, the follower, on the basis of the offered rates, decides the management of his home energy system including the load scheduling. The aim of this Lower Level (LL) problem is the minimization of the daily electricity bill. Since variation of the controllable loads with the respect to the ideal consumption procures a discomfort, a penalization term is also considered in the follower’s objective function. Different recent contributions propose BL formulations for the electricity pricing problem. For example, in (Grimm et al., 2021) the authors compare different pricing schemes and show that the RTP structure guarantees the highest additional revenue for the retailer, but also the largest price volatility for the prosumer. (Soares et al., 2020) propose a BL formulation where in the UL problem the retailer establishes the ToU tariff that maximizes the profit, whereas at the LL, the consumer, as follower, reacts to this price by determining the operation of the controllable loads in order to minimize the electricity bill and a discomfort cost. (Ferrara et al., 2021) propose a BL formulation where the leader owns a local energy production system to optimally manage, with the aim of reducing the amount of energy to purchase from the wholesale market to cover the follower request who is also equipped with a renewable energy system and can control the flexible loads. More recently, (Beraldi and Khodaparasti, 2023a) propose a BL formulation for defining RTP tariffs offered to a follower representative of a residential prosumager who reacts to price signal by scheduling the flexible appliances. Unlike other contributions, the leader owns a local energy system that must be properly managed with the aim of maximizing the daily profit. The contributions mentioned above share the assumption of perfect information of the parameters involved in the decision process, thus neglecting the impact that uncertainty in market prices and weather-related variables may have in defining the optimal tariff. Only a few recent contributions, acknowledging the importance of explicitly dealing with uncertainty, propose stochastic BL formulations. Here, we mention the recent contribution by (Beraldi and Khodaparasti, 2023b) who propose a stochastic formulation for the definition of time-variant tariffs. Specifically, the leader solves a two-stage problem to define the optimal procurement plan, considering both the day-ahead and the real-time market, and maximizing a safety measure that controls the expected profit that can be gained in a given percentage of worst case realizations. The follower reacts to the offered tariffs by optimally managing his home energy system with the aim of reducing the expected electricity bill. In (Sarfarazi et al., 2023) the authors provide a stochastic BL formulation where the aggregator sets real-time selling and buying prices, whereas users modify their consumption and their grid feed-in through the use of battery storage systems, to minimize their costs. Scenario based framework is introduced to take into account the uncertainty about market prices, local market generation levels and user electricity demand. In (Feng and Ruiz, 2023) a stochastic BL approach to determine electricity tariffs for energy community members is proposed. Proactive prosumers are assumed to be equipped with PV panels, storage devices and hydrogen systems. Although stochastic BL formulations have been shown to perform better than their deterministic counterparts (Beraldi and Khodaparasti, 2023b), their solution poses severe computational challenges. Deterministic BL problems have been proved to be NP-hard, thus the explicit consideration of uncertainty introduces an additional layer of complexity, preventing the solution of large-scale instances that take into account a significant number of possible future scenarios. Nevertheless, the pricing problem should be solved on a daily basis to generate electricity rates for the following day, thus imposing a limit on the computational time. To address this challenge, we incorporate uncertainty into the decision process by employing forecasts of the random parameters (Samal et al., 2021). In particular, we assume to know the wholesale electricity prices as they are announced in advance one day-ahead, whereas weather-related variables, i.e. the solar production, are considered as random and are forecast. The proposed approach relies on the idea of integrating prediction and optimization. In particular, we apply the classical ”predict, then optimize” paradigm, where prediction is performed first and then the forecast values are used in the BL optimization model. A strong advantage of the considered approach compared to more advanced frameworks that jointly perform predictions and optimization relies on the observation that the optimization problem is not "altered". This represents an important element in our case given the difficulty related to the solution of the BL problems. The contributions of this paper are summarized below:

- We apply machine learning (ML) techniques to derive day-ahead accurate PV power production forecasts serving as input parameters for the BL model.
- We formulate and solve the learning powered BL formulation once derived the corresponding single level reformulation.
- We test the proposed approach on a realistic case study and we derive useful insights.

The rest of the paper is organized as follows. Section 2 outlines the proposed methodology: first, we detail the techniques used for PV prediction, and, then, we present the BL formulation, followed by the used solution approach. Numerical results of experiments carried out on a realistic case study are presented and discussed in Section 3. Conclusions and future research directions are discussed in Section 4.

2 THE PROPOSED APPROACH

We consider an aggregator facing the problem of defining electricity rates for a homogeneous group of smart prosumers represented by a reference prosumager. As the aim is to offer RTP rates, the problem has to be solved every day, using each time updated information. Figure 1 shows the scheme of the proposed approach. It consists of two main modules. In particular, Module 1 refers to the forecast of the uncertain parameters entering as input of Module 2, where rates are determined by the solution of a BL problem. Boxes under the two modules refer to the solution techniques. Specifically, Machine Learning is used for forecasting, whereas the solution of the BL problem is carried out by using a commercial solver once that a single-level reformulation is obtained.

2.1 Forecasting the Solar Production

In the last decades, several methods have been proposed for PV power prediction (Ahmed et al., 2020). The methods are based on two main approaches: the physical approach and the data-driven one. While the former requires prior knowledge of the PV material

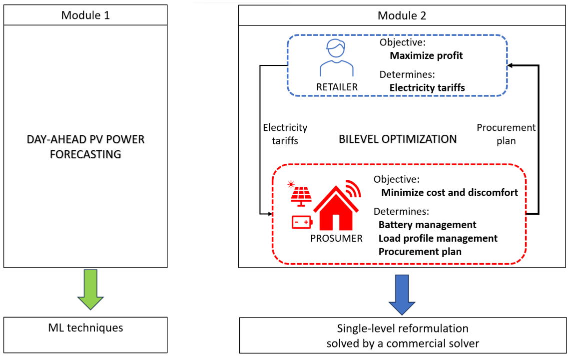

Figure 1: Structure of the proposed approach.

properties and the metadata, along with the need of weather condition data, the latter requires operational data to train/calibrate the coefficients of the models which are then used to generate the predictions. In this paper, we focus on day-ahead solar power forecasting. Specifically, the PV production of the next day is generated one day in advance. We adopt the data-driven approach and, specifically, we apply forecasting techniques belonging to the class of Machine Learning, as they provide (see, e.g. (Das et al., 2018)) better results, although they are more computationally demanding. In particular, we consider four ML techniques: Multivariate Linear Regression (MLR), Support Vector Regression (SVR), Random Forest (RF) and Artificial Neural Networks (ANNs).

- MLR: It is a simple and widely applied model in solar forecasting. Specifically, the MLR forecasts the PV production by considering a linear relationship between the target variable and a set of independent variables (predictors). In our case, the slope and the intercept are determined in the training phase minimizing the sum of squared residuals between the predicted values and the actual values, according to the Ordinary Least of Squares (OLS) algorithm.
- SVR: It is a kernel based forecast technique that evolved from the Support Vector Machine, which is typically used for classification problems. Similar to SVM, the SVR constructs a set of hyperplanes in a multidimensional space in order to derive the relationship between predictors and the target variable. In this study, we consider the Radial Basis kernel function (Scott et al., 2023).
- ANN: The architecture of the ANNs allows to build complex nonlinear relationships between predictors and the target variables, without assuming any form of relationship between these variable. ANN consists of an input layer that receives the input data, and an output layer that provides the predictions. Moreover, there is a

predefined number of hidden layers that transform the weighted sum of inputs, using an activation function. In this study, we consider a back-propagation algorithm to learn the weights that minimize the difference between the actual values of target variable and the resulting values of output layer of the net.

- RF: Random forest is an ensemble method that combines the results of multiple decision trees to determine the result. The training set is recursively partitioned to classify the target data on the basis of one or more predictor variables, generating a number of trees. A tree generated may be identical or different to another tree generated during the execution of the algorithm. Only one tree is selected and used to make the prediction, and the selection is made using the majority voting criterion: the most frequent tree is selected. The tree generation algorithm is implemented using the Gini index and the minimum number of elements in a leaf node as stopping criteria.

2.2 The BL Formulation

Forecasts generated by applying the algorithms introduced in the previous subsection represent the values in input to Module 2, where electricity rates are determined by applying the BL formulation. We assume to consider hourly-rate and we denote by r_t the rate offered by the aggregator at time period t of a given planning horizon (1 day). Bound constraints are imposed on the offered rates:

$$R_t^{min} \leq r_t \leq R_t^{max} \quad \forall t \tag{1}$$

Here R_t^{min} is a lower bound defined increasing the average market prices by a percentage accounting for taxes and leverages, whereas R_t^{max} accounts for market competition and eventual caps agreed with the follower in advance. Moreover, we impose a threshold Γ on the average price that can be reached during a day:

$$\frac{1}{T}\sum_{t=1}^{T} r_t \leq \Gamma \tag{2}$$

The aim of the leader is to maximize the daily profit defined as difference between revenues deriving from the electricity selling and procurement costs, i.e. purchasing electricity from the market.

$$\max F = \sum_{t=1}^{T} (r_t E_t - P_t^M E_t) \tag{3}$$

Here P_t^M denotes the market prices, whereas E_t denotes the energy amount required by the follower. Such a variable is not under the leader control, but for given values of the electricity rates represents the solution of the LL problem. Specifically, the follower reacts to the offered rates by managing the home energy system composed by a BES of a given nominal capacity C and a system of PV panels with a power production G_t forecast by Module 1. The aim is to minimize the daily electricity bill by exploiting the stored electricity and the load flexibility. In particular, we assume that the follower's loads are partitioned into inflexible and flexible loads on the basis of their level of control. Inflexible demand or base load is associated with a consumption that cannot be controlled (e.g. refrigerators, centralized heating and cooling systems, lighting for essential areas), whereas flexible demand refers to an energy consumption that can be shifted. For a given time period t, ideal flexible load value is denoted by x_t^{id}, whereas we denote by w_t the base load. Variation from the ideal consumption produces a discomfort that should be also taken into account in the follower's objective function. For each period t of the time horizon, the prosumager has to take three types of decision on:

- the amount to buy from the retailer E_t;
- the operation of the flexible loads, controlled by the variables x_t, x_t^+, x_t^-;
- the management of the BES, represented by the state of charge, soc_t, and the power charged z_t^c, and discharged from the battery z_t^d.

The following constraints are included into the LL problem:

$$x_t = x_t^{id} + x_t^+ - x_t^- \quad \forall t \quad (h_{1t}) \tag{4}$$

$$\sum_{t=1}^{T} x_t = \sum_{t=1}^{T} x_t^{id} \quad (h_2) \tag{5}$$

$$w_t + x_t \leq Q \quad \forall t \quad (h_{3t}) \tag{6}$$

$$E_t = x_t + w_t - G_t - z_t^d + z_t^d - z_t^c \quad \forall t \quad (h_{4t}) \tag{7}$$

$$\text{soc}_t = (1-\alpha)\,\text{soc}_{t-1} + \eta_c z_t^c - \frac{z_t^d}{\eta_d} \quad \forall t \quad (h_{5t}) \tag{8}$$

$$\mu_1 C \leq \text{soc}_t \leq \mu_2 C \quad \forall t \quad (h_{6t}, h_{7t}) \tag{9}$$

$$z_t^c \leq \tau_c C \quad \forall t \quad (h_{8t}) \tag{10}$$

$$z_t^d \leq \tau_d C \quad \forall t \quad (h_{9t}) \tag{11}$$

$$E_t, x_t, x_t^+, x_t^-, z_t^d, z_t^c \geq 0 \quad \forall t \tag{12}$$

Constraints (4) refer to the flexible loads and model the hourly deviation between the ideal consumption, whereas constraints (5) ensure that, considering the entire time horizon, the total consumption is satisfied. An upper bound Q on the consumption of the follower, is set by constraint (6), for each period t of the time horizon. The amount of electricity to purchase from the leader is defined by constraints (7). Besides PV production, demand can be covered by the power discharged from the BES, whereas the amount in excess is stored and used later. Constraints (8) refer to the management of the BES considering a self-discharge rate α, a charging efficiency η_c and a discharging efficiency η_d. The initial condition for the state of charge of the battery is defined as $soc_0 = \mu_1 C$. Constraints (9) guarantee that the state-of-charge of the battery, soc_t, remains within minimum and maximum levels, determined as a function of the nominal capacity C through the coefficients μ_1 and μ_2, while constraints (10)–(11) set upper bounds on the total power charged and discharged, defined as a percentage (charging rate τ_c and discharging rate τ_d) of the nominal capacity. Given the communicated rates r_t, the aim of the follower is to minimize the objective function:

$$\min f = \sum_{t=1}^{T} [\, r_t\, E_t \; + \rho_1 x_t^- \; + \rho_2\, x_t^+ \,] \tag{13}$$

Here, two goals are considered related to the cost and discomfort, respectively. This latter corresponds to the figurative cost of changing the consumption pattern from the ideal one. More in detail, the figurative cost is defined by penalizing positive (x_t^+) and negative (x_t^-) deviations of the actual load from the preferred value x_t^{id} through the coefficients ρ_1 and ρ_2.

2.2.1 The Solution Approach

To solve the proposed BL formulation we apply a traditional approach relying on the derivation of a single level reformulation. We note that for fixed values of the electricity rates r_t, the LL problem is a linear problem. We can therefore derive the corresponding dual problem reported below:

$$\begin{aligned}\max z = & \sum_{t=1}^{T} h_{1t}\, x_t^{id} + h_2 \sum_{t=1}^{T} x_t^{id} + \sum_{t=1}^{T} h_{3t}\,(w_t - Q) \\ & + \sum_{t=1}^{T} h_{4t}\,(G_t - w_t) + h_{51}\, soc_0\,(1-\alpha) + \\ & + \mu_1\, C \sum_{t=1}^{T} h_{6t} + - \mu_2\, C \sum_{t=1}^{T} h_{7t} + \\ & - \tau_c\, C \sum_{t=1}^{T} h_{8t} - \tau_d\, C \sum_{t=1}^{T} h_{9t}\end{aligned} \tag{14}$$

$$s.t.$$

$$-\, h_{4t} \leq r_t \;\; \forall t \tag{15}$$

$$h_{1t} + h_2 - h_{3t} + h_{4t} \leq 0 \;\; \forall t \tag{16}$$

$$h_{1t} \leq \rho_1 \;\; \forall t \tag{17}$$

$$-\, h_{1t} \leq \rho_2 \;\; \forall t \tag{18}$$

$$h_{4t} - \eta_c\, h_{5t} - h_{8t} \leq 0 \;\; \forall t \tag{19}$$

$$-h_{4t} + \frac{1}{\eta_d}\, h_{5t} - h_{9t} \leq 0 \;\; \forall t \tag{20}$$

$$\begin{aligned} & h_{5t} - (1-\alpha)\, h_{5\,t+1} + \\ & + h_{6t} - h_{7t} = 0 \;\; \forall t \in \{1,\, T-1\}\end{aligned} \tag{21}$$

$$h_{5T} + h_{6T} - h_{7T} = 0 \tag{22}$$

$$h_{1t},\, h_2,\, h_{4t},\, h_{5t}\ free \tag{23}$$

$$h_{3t},\, h_{6t},\, h_{7t},\, h_{8t},\, h_{9t} \geq 0 \tag{24}$$

We observe that the LL problem is always feasible and bounded. Thus, based on the strong duality theorem, both the primal and the dual problems have optimal solutions and the corresponding objective function values are equal. The single-level reformulation is obtained by adding to the UL constraints, the primal LL constraints (4)-(12), the corresponding dual constraints (15)-(24) and equating the primal (13) and dual objective functions (14). We observe that the single-level reformulation contains a bilinear term deriving from the product of the r_t and E_t variables, that we may linearize by adopting a dual approach. More specifically, the auxiliary variable $\omega_t = r_t\, E_t$ is introduced, together with the following set of constraints:

$$r_t = (\lambda_1 + \lambda_2) L_1 + (\lambda_3 + \lambda_4) U_1 \tag{25}$$

$$E_t = (\lambda_1 + \lambda_3) L_2 + (\lambda_2 + \lambda_4) U_2 \tag{26}$$

$$\sum_{i=1}^{4} \lambda_i = 1 \tag{27}$$

$$\omega_t = \lambda_1\, L_1\, L_2 + \lambda_2\, L_1\, U_2 + \lambda_3\, U_1\, L_2 + \lambda_4 U_1\, U_2 \tag{28}$$

$$\lambda_i \geq 0 \;\; i = 1,\, \ldots,\, 4 \tag{29}$$

where L_1 and U_1 are defined from 1, while L_2 is assumed to be 0, and U_2 to be equal to the prosumer's maximum total consumption Q.

3 NUMERICAL RESULTS

This section is devoted to the presentation and discussion of the computational experiments carried out to assess the effectiveness of the proposed approach on a realistic case study. The techniques used to forecast the PV power production have been implemented by using the software R version 4.3.0 (R Core Team, 2023), whereas the model and the solution algorithm have been coded in GAMS 38 and solved using ILOG CPLEX (Bussieck and Meeraus, 2007). All the experiments have been performed on a 64-bit HP Pavilion Laptop 15-eg2xxx with 12th Gen Intel(R) Core(TM) i7-1255U 1.70 GHz and a RAM of 16 GB.

3.1 Case Study and Data Setting

The case study concerns a retailer operating in the Italian electricity market that wants to offer RTP tariffs to affiliated end users, represented by a reference prosumager. The tariffs are communicated the day before the commitment and are, therefore, dynamically determined. Following the organization of the Italian market, we consider hourly time steps. The results reported in the following refer to an autumn day, specifically $30th$ October 2019, for which the real values are available. In particular, day-ahead electricity prices are available on the website of the Italian "Gestore dei mercari elettrici"(GME)[1] for download. Starting from these values, proper bounds on the rates have been determined. R_t^{min} has been set to $R_t^{min} = \min_{t \in T} P_t^M \ (1+\beta)$, whereas $R_t^{max} = \max_{t \in T} K \ P_t^M \ (1+\beta)$. Finally, $\Gamma = U \ (1 + \beta) \frac{1}{T} \sum_{t=1}^{T} P_t^M$, where β, K and U are parameters under the decision maker control. In our experiments, we have considered the values 1.3, 1.2 and 1.2, respectively.

Tariffs are offered to a reference prosumager, who reacts to the price signals by managing his domestic energy system with the aim of minimizing the electricity bill. In the experiments, we have considered a reference prosumager with an energy system composed of a BES with nominal capacity of 3.8 kW and a system of PV panels. Technical parameters concerning the management of the BES are reported in the Appendix, together with other parameters defining prosumer features. The amount of electricity the follower purchases from the leader depends on his self-production that is forecast. In the experiments, we have considered a reference PV module whose main characteristics are reported in the note [2]. Prediction has been carried out considering four main predictor variables, i.e. hour of the day, relative humidity (%), temperature (°C), radiance on tilt surface. As each predictor varies in different scale, a normalization step has been preliminary carried out. The data span a period of 3 years, from 01/01/2017 to 31/12/2019, for a total of 23832 records. The data set has been divided into two subsets, with observations from 2017 and 2018 used for the training and validation phases, and data from 2019 used for testing. Approximately 57% of the data set is used as the training set, a further 6% as the validation set and the remaining 37% as the test set. The ML techniques have been evaluated by using three traditional metrics: the root mean square percentage error (RMSPE), the mean absolute percentage error (MAPE), and R squared (R^2). More specifically, the metrics are defined as:

Table 1: Performance metrics of the ML techniques.

ML technique	RMSPE	MAPE	R^2
MLR	23.5	11.4	97.2
SVR	10.8	**5.5**	**97.9**
ANN	46.2	31.9	93.4
RF	**9.7**	5.7	97.5

$$RMSPE = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \left(\frac{y_j - \hat{y}_j}{y_j} \right)^2}$$

$$MAPE = \frac{1}{M} \sum_{j=1}^{M} \left| \frac{y_j - \hat{y}_j}{y_j} \right|$$

$$R^2 = 1 - \frac{\sum_{j=1}^{M} (y_j - \hat{y}_j)^2}{\sum_{j=1}^{M} (y_j - \bar{y})^2}$$

Here M denotes the number of data points of the test set, whereas y_j, $\hat{y}_j$ represent the j-th actual and predicted value. Finally, $\bar{y}$ denotes the expected value of the target variable. Better performance are associated with lower values of the RMSPE and MAPE and higher values of R^2. The results are reported in Table 1. As evident, the MLR and ANN techniques perform poorly, while the other methods provide accurate forecasts. Specifically, the SVR technique outperforms the other methods, reporting the lowest MAPE value and the highest value of R^2. Moreover, it also ranks second in the RMSPE metric. The RF method also performs well on the RMSPE metric and provides comparable values for the other two metrics.

Accuracy can be also appreciated by looking at the plot in Figure 2 where we report the real production in comparison to forecast one obtained by applying the different techniques. Looking at the Figure, we may note that the ANN tends to overestimate the PV production in the central hours of the day.

Forecast values are used by the leader who, in defining the electricity tariffs, anticipates the prosumager reaction. Clearly errors in the prediction negatively impact on his profit requiring the recourse to balancing market to compensate any shortage and/or surplus deriving from a difference between the initial requirement and the real ones.

3.2 Results of the BL Formulation

Different experiments have been carried out as function of the technique used to forecast the PV produc-

[1] https://www.mercatoelettrico.org/it

[2] Schuco module, series MPE 240 PG 60 FA with size 1.995 x 998 mm, nominal power equal to 240 W, under standard test condition

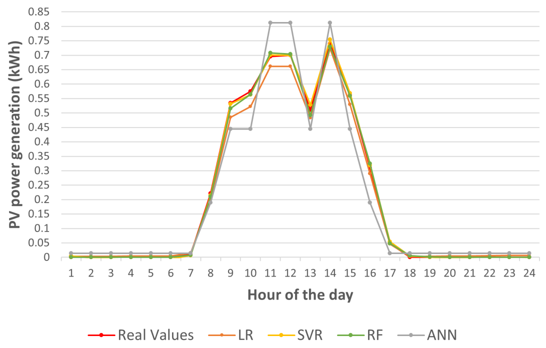

Figure 2: Actual vs. predicted PV Production.

tion. The results have been compared with those obtained when considering the real data to gain insight on the impact of the prediction accuracy on the recommendation provided to the end-user. In what follows, we report the results obtained adopting the SVR technique that, at least considering the data used here, represents the most performing approach. Similar results have been obtained considering the other techniques, which provide anyhow good predictions. Figure 3 shows the electricity tariffs offered by the leader, ranging from 9.82 c€/kWh to 16.99 c€/kWh. In the same Figure we also report the wholesale electricity prices. As evident, the rates and prices show a similar trend.

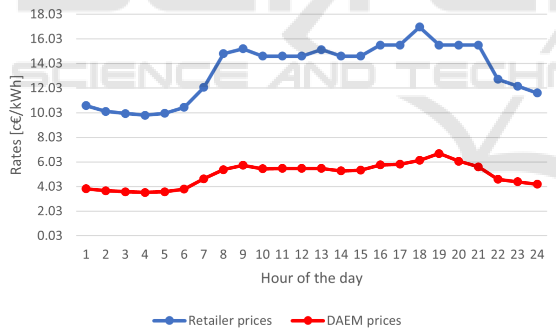

Figure 3: Offered rates and DAEM prices.

Given the offered tariffs, Figure 4 shows the reaction of the follower. Specifically, we report the consumption pattern after performing eventual shifting of the flexible loads and we show how the demand is satisfied. In detail, in high price periods 8, 9, 20 and 21, the ideal loads are partially shifted towards period 4, which is characterised by the minimum price, and periods 3 and 5, which present the second and the third lowest values. The solution indicates to shift the 59.4 % of the total flexible demand. Moreover, in these high price hours, the demand is also met by discharging the battery, which is charged through the electricity supply in period 4 and 15 and with the PV generation when this overcomes the demand of the same period.

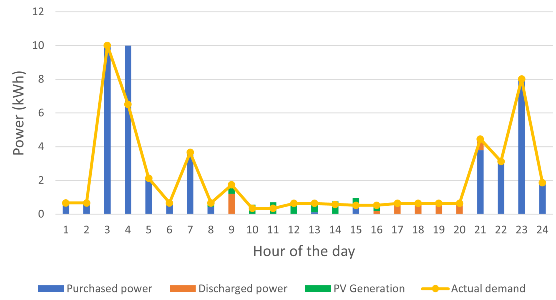

Figure 4: Prosumager's demand satisfaction.

Additional experiments have been performed with the aim of measuring the impact of the forecast techniques on the leader's strategy. More specifically, we have compared the cost of the leader's supply plan when considering the real PV production and when considering the different prediction techniques. The results show that the increase is very low for all the techniques , which the exception of the ANN one. In that case, at least for the case study considered in our tests, an increase of around 4 % has been registered. Clearly, the higher the share of the renewable production, the higher the negative effect produced by not accurate prediction.

4 CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The paper presents a BL approach for the pricing problem faced by an aggregator who wants to determine real time electricity rates to offer to aggregated end-users represented by a reference prosumager. The problem is solved every day using, each time, more updated information and the offered rates are communicated the day-ahead. Uncertainty in weather-related variables is dealt by applying ML techniques that provide accurate forecast which are then used as input data for the BL problem. This predict and optimize approach allows to explicitly account for uncertainty keeping the original structure of the BL problem. The problem is solved by a commercial solver once derived the corresponding single-level reformulation. Several experiments have been carried out to assess the efficiency of the proposed approach on a realistic test case, where the leader is presented by a retailer operating in the Italian electricity market and the follower is a prosumager owing a domestic energy system. Specifically, the performance of the four ML techniques has been measured and compared by applying traditional measures. The results show that all the methods provide accurate forecast, especially the SVR and the RF approaches. The experiments show how the quality of the forecasts impacts on the recommendations provided by the model when implemented on a real setting. Inaccurate predictions impose the recourse to the balancing market to compensate any shortage/surplus of the required power, determining a reduction of the leader's profit. Different issues are currently under investigation and represent future developments. First of all, the BL problem can be extended to a multi-follower setting so to consider a more general configuration where different types of followers are jointly considered and the leader can offer specialized tariffs. The problem would be more complex if we consider the possibility that the followers may sell energy to the aggregation. An additional interesting extension would be to define comprehensive tariffs that cover both electricity and gas by exploiting the close relationship between the two markets.

ACKNOWLEDGEMENTS

We acknowledge the financial support from: PNRR MUR project PE0000013-FAIR .

REFERENCES

Ahmed, R., Sreeram, V., Mishra, Y., and Arif, M. (2020). A review and evaluation of the state-of-the-art in pv solar power forecasting: Techniques and optimization. *Renewable and Sustainable Energy Reviews*, 124:109792.

Beraldi, P. and Khodaparasti, S. (2023a). A bi-level model for the design of dynamic electricity tariffs with demand-side flexibility. *Soft Computing*, 27:12925–12942.

Beraldi, P. and Khodaparasti, S. (2023b). Designing electricity tariffs in the retail market: A stochastic bi-level approach. *International Journal of Production Economics*, 257(108759).

Bussieck, M. R. and Meeraus, A. (2007). Algebraic Modeling for IP and MIP (GAMS). In *Annals of Operations Research*, volume 149(1), special edition History of Integer Programming: Distinguished Personal Notes and Reminiscences, Guest Editors: Kurt Spielberg and Monique Guignard-Spielberg, pages 49–56. Kluwer Academic Publishers-Plenum Publishers.

Colson, B., Marcotte, P., and Savard, G. (2007). An overview of bilevel optimization. *Annals of operations research*, 153(1):235–256.

Das, U. K., Tey, K. S., Seyedmahmoudian, M., Mekhilef, S., Idris, M. Y. I., Van Deventer, W., Horan, B., and Stojcevski, A. (2018). Forecasting of photovoltaic power generation and model optimization: A review. *Renewable and Sustainable Energy Reviews*, 81:912–928.

Feng, W. and Ruiz, C. (2023). Risk management of energy communities with hydrogen production and storage technologies. *Applied Energy*, 348:121494.

Ferrara, M., Violi, A., Beraldi, P., Carrozzino, G., and Ciano, T. (2021). An integrated decision approach for energy procurement and tariff definition for prosumers aggregations. *Energy economics*, 97(105034).

Grimm, V., Orlinskaya, G., Schewe, L., Schmidt, M., and Zöttl, G. (2021). Optimal design of retailer-prosumer electricity tariffs using bilevel optimization. *Omega*, 102(102327).

R Core Team (2023). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Samal, D., Bisoi, R., and Sahu, B. (2021). Identification of nonlinear dynamic system using machine learning techniques. *International Journal*, 12(1):23–43.

Sarfarazi, S., Mohammadi, S., Khastieva, D., Hesamzadeh, M. R., Bertsch, V., and Bunn, D. (2023). An optimal real-time pricing strategy for aggregating distributed generation and battery storage systems in energy communities: A stochastic bilevel optimization approach. *International Journal of Electrical Power & Energy Systems*, 147:108770.

Scott, C., Ahsan, M., and Albarbar, A. (2023). Machine learning for forecasting a photovoltaic (pv) generation system. *Energy*, 278:127807.

Soares, I., Alves, M. J., and Antunes, C. H. (2020). Designing time-of-use tariffs in electricity retail markets using a bi-level model – estimating bounds when the lower level problem cannot be exactly solved. *Omega*, 93:102027.

APPENDIX

In the numerical experiments, we have used the following parameters in the constraints related to the storage management. In particular, the values of the efficiency rates i.e. η_c, η_d have been set to 0.98, whereas the operation ranges are set to $\mu_1 = 5\%$ and $\mu_2 = 95\%$. Finally, the charging and discharging coefficients (τ_c, τ_d) have been set equal to 95% of the BES capacity C. The values of base load w_t and ideal flexible load x_t^{id}, for each period of the time horizon, have been derived from data reported in (Soares et al., 2020). The maximum total prosumer's consumption (Q) is set to 10 kWh, whereas the parameters ρ_1 and ρ_2 are assumed to be equal to 0.01 and 0.005, respectively.