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Power purchase agreements for plus energy neighbourhoods: Financial risk mitigation through predictive modelling and bargaining theory ☆

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ABSTRACT

This paper introduces a continuous 24/7 power purchase agreement (PPA) designed for contracting photovoltaic (PV) generation within sustainable plus energy neighbourhoods (SPENs) or local energy communities, aiming to ensure a stable economic revenue stream for community stakeholders. The PPA involves the sale of solar PV generation, auctioned at a fixed strike price, to an external off-taker. Employing statistical prediction tools such as long short-term memory and auto-regressive modelling, the proposed framework allows hour-to-hour power delivery commitments between seller and buyer, accurately estimating the agreed-upon volume of renewable energy to be exchanged. A fixed PPA price is negotiated utilizing Nash Bargaining Theory, aiming to optimize revenue for the SPEN while minimizing procurement costs for the buyer, thus achieving an economic equilibrium that mitigates the long-term price risk prevalent in wholesale energy markets. Additionally, the proposed methodology includes utilization of a battery energy storage system (BESS) to store excess power or address supply–demand contractual disparities during periods of low PV generation. Simulation results obtained under varying climatic conditions and energy market dynamics across different countries, demonstrate that the proposed PPA framework, by combining risk assessment strategies and statistical learning methods, can effectively reduce associated financial risks while maximizing payoff for the community.

1. Introduction

The advent of information technologies have allowed conventional consumers to become prosumers by investing on local production of generation at their premises. Local energy communities (LECs) expand this idea to bring together several prosumers to pool their energy resources. These LECs are typically formed by a group of stakeholders, including household consumers, businesses, or public entities, situated in a specific geographical area, who collaboratively produce, consume, and exchange locally generated renewable energy. Consequently, LECs not only promote a greener and more sustainable energy future, but they also serve as a potent instrument for energy cost reduction, enabling consumers to take an active role in energy markets and reap direct financial benefits. For instance, LECs can leverage power purchase agreements (PPAs) to ensure stable and long-term revenue streams and foster economic sustainability. One emerging approach is '24/7' renewable PPAs, which aim to match the hourly generation of the seller to the hourly consumption at the buyer's side [1].

PPAs are conventionally used to ensure availability of generation capacity irrespective of the electricity off-take [2]. For the buyer, there is no longer a dependency on strongly fluctuating electricity market prices in the event of high demand. A PPA can still enable communities to hedge their generation revenue against long term price risks. Due to the long duration of months or years, PPAs also provides financial security that can attract investment, fund operational costs, and facilitate the expansion of renewable energy installations within a community [3]. However, PPAs run the risk of quantity uncertainty due to renewable generation intermittency at the seller's side [4]. This could potentially be averted by risk averse bids from the seller, in particular by underbidding its future generation profile to be supplied to the buyer [5]. This would imply that the buyer would contract less in PPA from the LEC, and thereby purchase more from the energy markets directly.

To reduce this exposure of seller-buyer pair to the uncertainties of electricity markets, statistical learning tools can also be availed. In particular, improved prediction techniques can be used to estimate the

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long-term generation volumes of a PV generation, thereby allowing better decision making for long-term power contracts under PPAs. It is known that PV generation can be predicted several hours ahead with reasonable accuracy [6,7]. As solar irradiation is stochastic, specifically due to weather events, state space models have been proposed in the literature to characterize the noise in the PV power to improve prediction [8]. To this purpose, machine learning techniques are well suited for prediction of time series data sets. Therefore, considering the historical PV generation as sequential data sets dependent on spatial and weather conditions, recurrent neural networks (RNNs) can be trained to predict monthly solar photovoltaic power generation at any specific site [9]. In particular, long-short-term-memory (LSTM) networks, a variant of RNNs, are commonly investigated in literature to investigate PV generation capabilities for short or long time duration as described in [10,11].

Long-term PV prediction, essential for capturing trends and seasonal variations in generation output [12], requires balancing strategies for hourly generation within '24/7' PPA contracts. The variability of PV generation can lead to periods of under or over-production, forcing the buyer to adjust power procurement from the energy markets [13,14]. This market unpredictability contrasts with the stability of long-term PPAs. To mitigate these challenges, the use of battery energy storage systems (BESS) is crucial [15]. BESS not only helps in aligning generation with load requirements but also enhances the financial resilience of LECs [16]. Optimal BESS sizing and scheduling can offer benefits like micro-grid balancing [17] and efficient short-term energy delivery [18], making it a vital component in the PPA ecosystem.

The determination of the PPA strike price is a critical factor in securing a mutually beneficial contract between the LEC and the buyer. On these lines, Nash Bargaining Theory provides an effective method for energy price negotiations [19], ensuring that the interests of both parties are equitably addressed. Accordingly, the negotiated PPA strike price is the outcome of a bargaining process where both parties strive to optimize their individual utility functions [20]. The PV generator, within the LEC, would aim for a price that is higher than its levelized cost of energy (LCOE) to ensure profitability [21]. Conversely, the buyer would ideally want a strike price that is lower than the prevailing market prices to realize cost savings in the PPA. By applying game theoretical concepts, a consensus can be reached where the negotiated strike price balances the requirements of both parties based on their bargaining powers. This ensures that the LEC can profit from the PV generation while the buyer secures a cost-effective energy supply, ultimately creating a sustainable and economically viable PPA.

The flexibility in load consumption and demand response is pivotal in managing the inherent variability of PV generation for 24/7 PPAs [22]. This paper addresses the structuring of PPA contracts in two segments: (a) long-term considerations for PPA price negotiation and energy volume trading, and (b) short-term balancing of hourly energy requirements, facilitated by BESS. By implementing LSTM models trained on hourly data, we ensure reliable long-term PV generation predictions. Additionally, short-term forecasting inaccuracies are addressed using auto-regressive models. Together, these models balance the contracted energy volumes effectively. Furthermore, the integration of value at risk (VaR) analysis helps manage the economic risks associated with volume and price uncertainties, while Nash Bargaining Theory helps in formulating a balanced PPA pricing structure considering both buyer's and seller's risk tolerance.

It is evident from existing literature that suitable bilateral contractual settlement schemes are essential for 24/7 PPAs, with an emphasis on long-term certainty in energy volume and price. A 24/7 PPA is necessary to synchronize renewable generation with real-time consumption, ensuring balanced energy supply throughout the day and enhancing grid stability. This approach effectively manages the intermittency of PV, which is not adequately addressed in traditional long-term (yearly) PPAs. The conventional PPAs overlook the daily and seasonal variations in PV output, leading to potential demand-supply imbalances. In contrast, 24/7 PPAs focus on hour-to-hour delivery commitments, aligning PV generation with actual hourly demand. This would allow both the seller and buyer to initiate a risk free settlement supported by a stable long-term pricing mechanism.

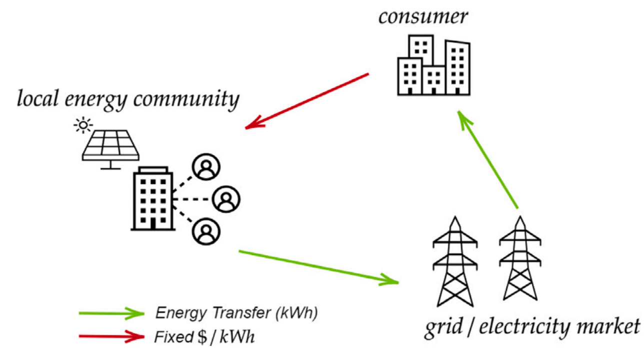

Fig. 1. Virtual PPA contract settlement between the seller LEC and an grid-connected buyer with energy balancing undertaken through electricity market.

Moreover, the role of flexibility using BESS in 24/7 PPAs, and its optimal sizing under varying renewable generation is an important step towards realizing bilateral PPA contracts. Accurate predictions of renewable energy production combined with risk measures such as VaR can provide low deviations of energy mismatches, thereby further saving flexibility requirements. Finally, as renewable PPA contracts include distinct economic preferences of the buyer and seller, cooperative solutions can be used to ascertain on fixing energy prices based on dynamic market prices.

Based on the aforementioned points, the novel contributions of this paper can be summarized as follows,

- The paper introduces an approach that combines the risk assessment concept of VaR with RNN based predictions for determining the energy trading volume for long-term forward contracts. This approach is designed for risk-averse off-takers and suppliers, bridging the gap between risk measurement and predictive analytics in the domain of energy trade.
- The paper outlines a methodology to derive an optimal pricing structure for long-term PPAs, based on cooperative bargaining solutions. The target of this approach is to ascertain an equilibrium PPA strike price that surpasses the marginal LCOE yet falls below wholesale market prices, thereby ensuring the maximization of long-term financial benefits for both parties involved in the settlement.
- The paper undertakes an exhaustive exploration of the impact of BESS flexibility on PV volumetric uncertainties related to hourly base-load PPAs. The analysis accounts for market-related risks, specifically fluctuations in long-term wholesale prices and uncertainties in renewable energy generation. The goal is to ascertain the financial viability of using a BESS, considering energy balancing requirements, market dynamics and PV generation intermittency.
- The paper studies PPAs focusing on economic benefits of LECs and the potential need for 24/7 PPAs, as the uncertainties surrounding PV generation and market participation may deter smaller entities like LECs from committing to conventional PPAs. By including a variety of European countries in the analysis, this paper also offers comparative understanding of diverse climatic and market conditions impact these PPAs.

2. Problem formulation

This work considers an LEC equipped with a fixed PV generation capacity. Moreover, the representation of the LEC has been streamlined to consider it as a collective entity possessing a singular large-scale aggregated PV system, rather than comprising multiple prosumers with individual PV systems. The primary objective of this research is to propose a long-term contract negotiation approach between an energy seller (i.e. the LEC) and an external consumer, set at a fixed price per unit, as depicted in Fig. 1. The power grid acts as an authorized distributor, delivering energy from the supplier to the buyer [21]. Consequently, the energy flow from the LEC's PV generator is conveyed to the buyer's site via the grid, thereby incurring additional network charges and fees beyond the PPA strike price. The methodology for PPA contract settlement is divided into three distinct stages. Initially, the contracted PV generation volume to be sold is calculated. This is followed by negotiations on the fixed price, and finally, energy balancing mechanisms are set in place to ensure a 24/7 PPA is achieved with least interaction from the market.

2.1. Long term prediction of contracted PV generation volume

Generation forecasting is a critical task in any short or long term energy contract. In particular, accurate forecasting helps in maintaining supply demand equality, and also reducing the cost of power generation by conceptualizing more predictable bids of the future. Among various forecasting methods, LSTM networks, a type of RNN, have the ability to show promising results due to their ability to model and predict time series data. Using sequential data of PV generation as a time series input, the prediction of PV generation can be found using the LSTM training process with the following steps,

1. Forget gate: Using a sigmoid function σ, over the current input x_t and the previous output h_{t-1}.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

2. Input gate: Involves the sigmoid function and hyperbolic tangent ($tanh$) layer that creates a new candidate vector.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

3. Update of cell state: By forgetting the specified part of the previous state and adding the new candidate values.

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{4}$$

4. Output gate: Controls which the value in the cell state is used to compute the final output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \tanh(C_t) \tag{6}$$

Here, the input x_t to the LSTM network would be historical PV generation data. In general, the dimension of the input fed to the LSTM model at a time would depend upon the hyper-parameter referred to as lookback parameter. Optimizing the choice of lookback period allows the predictions to include a particular length of input to train the output. For long-term PV generation forecast, the lookback would ideally be chosen to be higher. Moreover, to produce a multi-variate LSTM model, other relevant features such as weather conditions (temperature, irradiance, etc.) can also be included with their correlation input values to the output PV generation. Thus, the LSTM network can be trained to predict the PV generation for the next time step, or several time steps ahead, based on the input sequence of historical data. Moreover, in order to provide adequate pre-processing of data in case of high noise, the use of smoothing function such as moving average with a window size k, i.e. $MA_t = \frac{1}{k}\sum_{i=0}^{k-1} x_{t-i}$ can be utilized. In effect, such data-smoothing can help in highlighting the long term trend of the PV generation data while suppressing the short term stochastic noise.

The LSTM network would also require a suitable loss function while training, such as the mean squared error (MSE) between the predicted and actual PV generation, and an optimization algorithm such as stochastic gradient descent or Adam optimizer. The weights of the LSTM network would be updated iteratively to minimize the chosen loss function. The accuracy of the LSTM-based PV generation forecasting model can be evaluated using various metrics, however, the loss function used during the training process is typically chosen to be RMSE, which is defined as,

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

where, $\hat{y}_i$ are the predicted values, and y_i are the actual values.

For several time steps prediction in advance, a closed loop model is necessary whereby the output of the LSTM at each time step is fed back into the LSTM as input for the next time step. However, this approach may suffer from accumulation of errors since each new forecasted value depends on the previous forecasts. This approach allows the LSTM to make multi-step ahead forecasts based on its own previous predictions. However, it should be noted that errors in closed loop predictions can accumulate over time, potentially leading to lower accuracy for longer forecast horizons. Thus, a long-term PV generation prediction timeline may have more errors, while smaller timescale predictions may be more accurate. To this purpose, we propose a methodology to re-adjust the long term PV generation predictions to promote accuracy, segregating them into monthly, daily and hourly forecasts.

The long-term hourly PV generation forecasting can be broken down into short-term monthly forecasts to improve accuracy. This approach leverages the temporal hierarchy of the data, where high-level monthly forecasts are divided into lower-level daily forecasts. It is assumed that the PV generation remains constant over the foreseeable years in the future. The process can be described as follows,

1. Monthly Forecasting: An LSTM model is trained to predict the total PV generation for each month based on the past monthly data. This model captures the monthly patterns and seasonal variations in the PV generation data.

$$M_i = LSTM(M_{i-1}, M_{i-2}, \ldots, M_{i-n}) \tag{8}$$

where, M_i is the PV generation for month i and n is the period of historical data.

2. Daily Forecasting: For each month, another LSTM model is trained to predict the PV generation for each day based on the past daily data. This model captures the daily patterns in the PV generation data as follows,

$$D_{t,i} = LSTM(D_{t-1,i}, D_{t-2,i}, \ldots, D_{t-n,i}) \tag{9}$$

where, $D_{t,i}$ is the total generation for the day t, corresponding to the month i.

3. Disaggregation: As the monthly prediction M_t has lesser time-steps to predict, they may be more accurate. Thus, the longer daily forecasts $D_{t,i}$ may be re-calibrated by a proportionality ratio to incorporate information from monthly forecast,

$$\hat{D}_{t,i} = \frac{D_{t,i}}{\sum_{j=1}^{30} D_{t,j}} M_t \tag{10}$$

This allows adjustments to capture both long-term monthly trends and short-term daily patterns in the PV generation data. It may be inferred that similar reasoning can also help with daily and hourly forecast re-adjustments. This disaggregation process ensures that the forecasts at different levels are consistent with each other.

2.2. Volumetric uncertainty reduction using value at risk

As the prediction of PV generation carries burden of risk, there may be additional requirement of adjusting the energy volume in the PPA forward contracts. In particular, due to non-zero RMSE outputs in long-term hourly PV generation forecasts, we advocate for using Value at Risk (VaR) to ensure contractual energy fulfilment in the PPA. VaR is a statistical technique used to measure and quantify the level of risk considering a pre-defined probability distribution of the uncertain variable. This metric is most commonly used to determine the extent and occurrence ratio of potential losses in their financial portfolios. In the context of a PPA, the concept of VaR can be used to limit the volumetric uncertainty which arises due to the unpredictable future generation of the PV plant. This uncertainty can be due to various factors such as weather conditions, equipment performance, etc.

Let the PV predictions for a particular day be denoted as $\mathbf{X}_{pr} = \left[X^1_{pr}, \dots, X^{24}_{pr}\right]$. A beta distribution function can be utilized to model the uncertainty in PV generation of any particular time-slot X_t as follows [23],

$$f(X_t) = \frac{\Gamma(\gamma_t + \beta_t)}{\Gamma(\gamma_t)\Gamma(\beta_t)} \; X_t^{(\gamma_t - 1)} \; (1 - X_t)^{\beta_t - 1} \tag{11}$$

where t represents the time, Γ is the gamma function, while γ_t and β_t are the probability shape parameters that can be calculated using historical PV generation data. Subsequently, given a predefined distribution function of PV uncertainty, the VaR can be calculated as follows,

$$VaR_\alpha = \mu - \sigma \cdot \Phi^{-1}(\alpha) \tag{12}$$

where, VaR_α is calculated at the confidence level α, μ is the mean and σ is the standard deviation of $f(X_t)$, while $\Phi^{-1}(\alpha)$ is the quantile function. The confidence level α represents the probability that the actual PV generation will exceed the VaR. Upon considering the defined confidence level, the seller can finalize the anticipated PV generation to be transacted with the buyer. This forecast, along with the probabilistic confidence level, helps in managing the volumetric uncertainty in PV generation and establishes a more stable foundation for the PPA contract. For finding the risk-assessed energy volume to be traded in a day in a 24/7 PPA, the joint probability distribution combining every hour can be calculated as follows,

$$f(X_1, \dots, X_{24}) = f(X_1)f(X_2)\dots f(X_{24}). \tag{13}$$

where, all hourly $f(X_t)$ are considered to be i.i.d random variables, and computing the VaR for this joint distribution provides a comprehensive risk assessment for the day. It is to be noted that the upper and lower bounds of generation power estimated using LSTM model forecasts the overall PV generation potential of the LEC, while using VaR to assess the risk associated with these forecasts focus on the overall PV generation potential.

2.3. PPA strike price negotiations

The Nash Bargaining Theory can be used to negotiate the PPA strike price between two parties, such as a renewable energy producer and a utility company. The goal of the negotiation is to reach a mutually beneficial agreement that maximizes the utility of both parties. The Nash Bargaining Solution (NBS) provides a solution to this bargaining problem. It is a pair of strategies, one for each party, such that no party can unilaterally change their strategy to improve their utility without decreasing the utility of the other party.

Let U_S and U_B be the utility functions of the two parties, and let S_1 and S_2 be their respective strategy sets. A pair of strategies (s_1^*, s_2^*), where $s_1^* \in S_i$ is a NBS if it satisfies the following condition for each party i,

$$U_i(s_i^*, s_{-i}^*) \geq U_i(s_i, s_{-i}^*) \quad \forall s_i \in S_i \tag{14}$$

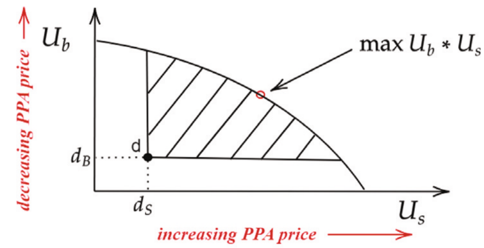

Fig. 2. Bargaining solution of the PPA strike price with seller and buyer utility functions (U_S and U_B) and disagreement points (d_S and d_B).

where, s_{-i}^* denotes the strategy of the other party.

In the context of PPA strike price negotiations, the strategies could represent different possible strike prices, and the utility functions could represent the net benefits of the parties from the PPA at those prices. The NBS would then represent the strike price that maximizes the net benefits of both parties and is therefore the most likely outcome of the negotiation. It should be noted that the NBS assumes that the parties are rational and have perfect information about each other's utility functions and strategy sets. In practice, these assumptions may not always hold, and the actual outcome of the negotiation may deviate from the NBS. The methodology for the PPA strike price negotiation can be explained using Fig. 2. It may be noted that both buyer and seller would want to maximize their own economic benefit, quantified using their respective utility functions. The seller LEC would want an high strike price whereas the buyer would want the price to be the lowest possible. Thus, PPA strike price should satisfy Pareto optimality, a condition that ensures no party can enhance their utility without compromising the utility of the other party. The Pareto-optimal solution favourable to both parties will be further discussed in the subsequent subsections.

2.3.1. LEC utility perspective

For a local energy community selling its PV generation in a PPA contract to an outside buyer, the utility function would represent the community's satisfaction or utility from the contract. This utility could depend on various factors such as the price received for the PV generation, the volume of PV generation sold, the stability of the buyer, etc.

A simple form of the utility function $U(p, v)$ with price p and volume v can be defined as follows,

$$U_S(p, v) = p \cdot v - C(v) \tag{15}$$

This function assumes that the community's utility is proportional to the net revenue from the PPA contract, i.e. price times energy volume minus the associated cost. The cost function $C(v)$ may include both volume-dependent variable costs and volume-independent fixed costs over PV lifetime T,

$$C(v) = \int_0^T \frac{C_t}{(1+r)^t} dt \tag{16}$$

The community would thus aim to maximize this utility function by negotiating a PPA contract that provides the highest price at a particular volume. Applying the first-order derivative condition to (15), we derive the following expression [24],

$$\frac{\partial}{\partial v} U_S(p, v) = p - C'(v) = 0 \tag{17}$$

where, the derivative $C'(v)$ increment in the present value of costs per additional unit of electricity generated, and can be considered to be the LCOE of PV generator. Thus, to keep the marginal gain in the utility of the LEC greater than zero, the minimum price by the LEC should be set at $p \geq C'(v)$. In this manner, the change in utility function $U_S(p, v)$ would remain positive for the LEC to participate in the PPA negotiation contract. Thus, (17) suggests that for maximizing utility,

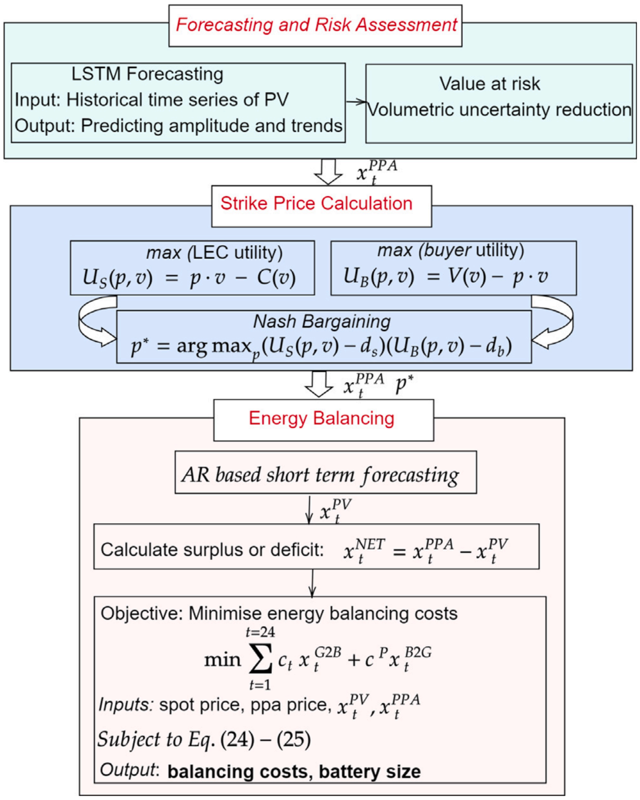

Fig. 3. Flowchart of three-stage settlement process of 24/7 PPA.

the price per unit of electricity should be set at least equal to the marginal cost of PV generation, that may include any variable and fixed costs. In other words, the satisfaction of (17) indicates the price at which the additional revenue from selling one more unit/kWh equals the additional cost of generating that unit.

2.3.2. Buyer's perspective

In the context of a buyer in a PPA contract, the utility function would represent the buyer's satisfaction or utility from the contract. This utility could depend on various factors such as the price paid for the PV generation, the volume of PV generation bought, the reliability of the PV generation, etc. A general formulation for buyer's utility can be defined as follows,

$$U_B(p, v) = V(v) - p \cdot v \tag{18}$$

where, the value function $V(v)$ could depend on both the volume and the reliability of the PV generation. The buyer would thus aim to maximize this utility function by negotiating a PPA contract at the lowest possible price. Moreover, using first order optimality condition on (18) we get,

$$\frac{\partial}{\partial v} U_B(p, v) = V'(v) - p = 0 \tag{19}$$

which shows that the marginal utility of the seller would only register a positive change if $V'(v) \geq p$. Moreover, it also reflects equilibrium point for the buyer's problem, where the price should not exceed the marginal utility $V'(v)$. In other words, the price the buyer would be prepared to pay for the PPA contract should be less than the marginal change in its perceived value, $V(v)$. The buyer seeks an electricity price that is less than its perceived real cost. As an alternative to the PPA, the buyer might resort to the wholesale electricity market to fulfil its energy requirements. Therefore, $V'(v)$ can also be interpreted as the average wholesale market price.

With the utility functions of the seller and the buyer as $U_s(p, v)$ and $U_b(p, v)$ respectively, the NBS is the price p^* for a particular pre-decided volume v^* that maximize the product of the utilities [25],

$$p^* = \arg\max_p (U_S(p, v) - d_s)(U_B(p, v) - d_b) \tag{20}$$

where, disagreement point is $d = (d_S, d_B)$ and d_S and d_B are the respective payoffs to the LEC and the buyer, which they are guaranteed to receive if they cannot come to a mutual agreement. In our case, the disagreement point for the LEC would be the scenario in which the PPA contract is not agreed upon by both parties due to failed price negotiations. In such a worst case scenario, the LEC may have to sell their PV generation at no-profit (i.e. LCOE) or average wholesale market price. In the absence of an agreement on the PPA with the LEC, the buyer's worst-case disagreement point would also be the wholesale electricity market price. This is the price the buyer would need to pay to procure the required power from the wholesale electricity market. This configuration of the disagreement points (d_S, d_B) reflects the worst-case scenario for each party if the PPA negotiations fail, i.e., the LEC and the buyer would both have to face market risk. However, the buyer and seller would place different risks in the future market prices, denoted as r_s and r_b. Using these, the disagreements points of the seller-buyer pair can be described as follows,

$$d_s = (\tau - r_s) \cdot v - C(v) \tag{21}$$

$$d_b = V(v) - (\tau - r_b) \cdot v \tag{22}$$

where, τ is the average market price predicted over the length of the contract. Thus, NBS ensures that both the LEC and the buyer have a strong incentive to reach an agreement, as they both stand to gain from a successful PPA negotiation compared to their worst-case disagreement scenarios.

The solution of (20) can be found by first order optimality condition, that is by setting the derivatives of the product with respect to price p equal to zero and solving,

$$\frac{\partial}{\partial p}[(U_S(p, v) - d_s)(U_B(p, v) - d_b)] = 0 \tag{23}$$

Alternatively, a PPA contract price can also be influenced by asymmetrical bargaining powers of either the seller or the buyer. The bargaining power of a seller can be derived from a unique value proposition which the buyer cannot easily find an alternative source to. In particular, if there is high demand for renewable energy but limited supply, the seller would have more bargaining power due to the scarcity of alternatives for the buyer. Furthermore, regulatory support, such as favourable government policies or incentives for renewable energy can enhance the LEC's bargaining power by making their offer more attractive to the buyer. On the other hand, the buyer's bargaining power can come from their market presence, alternative options, and financial resources. As a buyer, large organizations with significant market presence can have more bargaining power, as the seller may value the opportunity to establish a relationship with such a buyer. Defining the bargaining power of the seller-LEC and the buyer as $\vartheta \in [0, 1]$ and $1 - \vartheta$ respectively, the price negotiation using the NBS solution can be then denoted as,

$$p^* = \arg\max_p (U_S(p, v) - d_s)^{\vartheta} (U_B(p, v) - d_b)^{1-\vartheta} \tag{24}$$

where, higher value of ϑ would force the PPA strike price to be influenced by the seller, and vice-versa. The NBS takes these bargaining powers into account to find a fair and mutually beneficial agreement.

Fig. 3 illustrates the three-stage settlement process designed for 24/7 PPAs. In the first step we use LSTM to predict cyclic patterns and amplitudes of PV generation across different seasons. Following the LSTM predictions, VaR is utilized to quantify the risk associated with the forecasted PV generation. This risk assessment is used in determining the optimal volume of PV energy that can be sold daily under the PPA, striking a balance between maximizing energy sales and managing uncertainty. The second step is price determination, where we solve an unconstrained convex objective function as in (20) to derive a long-term fixed price for the PPA. This step ensures that the price point reflects both the seller's and buyer's economic interests through their utility functions. In the third step, we address the balancing requirements for hourly settlement by concentrating on the optimal charging and discharging of a BESS. For this purpose, a chance-constrained optimization framework is developed as detailed in the next subsection

2.4. Energy deficit balancing using BESS flexibility

BESS can play a crucial role in enabling the realization of 24/7 PPA between renewable energy seller and the buyer. In renewable energy contracts, the generation output may not always match with the long term contractual generation guarantees that would originally be formed. This discrepancy leads to a mismatch, causing a challenge to the continuous power supply requirement stipulated in PPA. In such a scenario, flexibility of consumption (and generation) provided through BESS provides a solution.

Initially, the LEC as the seller, utilizes an auto-regressive (AR) method for predicting the PV generation output for the forthcoming 24-h period. The AR method, using prior data points to forecast the future output, effectively captures the temporal dependencies in PV generation data. Hence, using historical days as the input, a pth order auto-regressive model can be formulated to forecast PV generation of the next day $x_1^{PV}, \dots, x_{24}^{PV}$ till as follows,

$$x_{t+1}^{PV} = \sum_{i=1}^{p} \phi_i \, x_{(t+1)-i}^{PV} + \varepsilon_t \tag{25}$$

where, ε_t is white-noise, and $\phi_1, \dots, \phi_p$ are modelling parameters estimated using Yule–Walker equations [26].

Once the PV generation for a typical day is forecasted, the seller then identifies the potential discrepancies between the anticipated PV generation and the contracted supply as per the 24/7 PPA. This step enables the seller to quantify the balancing requirements for the ensuing day, essentially outlining the degree of PV generation deficit or surplus anticipated at different time intervals. That is, considering the PPA contractual volume for any hour x_t^{PPA} and the hours-ahead PV generation forecast x_t^{PV}, the net deficit or surplus of PV generation will be,

$$x_t^{NET} = x_t^{PPA} - x_t^{PV} \tag{26}$$

where, both x_t^{PPA} and x_t^{PV} are known a-priori for the entire day. If x_t^{NET} is greater than zero, the LEC would be in a deficit of PV generation as contracted power supply exceeds the local PV generation. In such a scenario, the LEC would either balance the deficit by purchasing energy from the wholesale market or choose to discharge BESS.

Remark 1. Short term day-ahead forecasts of PV generation have reasonable accuracy as also discussed in [27]. Thus, this work considers the day-ahead PV prediction using AR to be accurate, and use it to calculate x_t^{NET} as in (26).

For balancing requirements at any typical day, an optimization framework can be established which aims to reduce the balancing costs of the LEC for the 24/7 PPA. Considering the hourly net x^{NET}, the LEC can procure the required balancing energy from the day-ahead energy markets at hourly varying spot prices. The objective of the LEC would be to reduce the purchase the least possible energy from the markets for fulfilling the PPA obligations,

$$\min \sum_{t=1}^{t=24} c_t \, x_t^{G2B} + c^P x_t^{B2G} \tag{27}$$

where, $\mathbf{c} = [c_1, \dots, c_{24}]$ are the hourly spot prices, c^P is the fixed PPA strike price, and $x_{t,c}^{G2B}$ and x_t^{B2G} are the 'grid to battery' (charging) and 'battery to grid' (discharging) variables for a particular time-slot t. In (27), the LEC pays hourly spot prices $\mathbf{c}$ while charging BESS, while the LEC receives the fixed PPA strike price c^P when discharging. This dynamic implies the BESS is solely utilized to supplement any deficit power under the PPA contract. Specifically, during hours when the spot price is cheaper, the BESS is charged, storing energy for subsequent use. In contrast, during periods when the contracted PV generation is expected to be more than the actual PV generated, the BESS discharges its stored energy. This strategic operation facilitates the consistent fulfilment of the PPA contract terms, despite the temporal discrepancies between the contracted and actual PV generation, thus optimizing the balance between supply and demand while also maximizing economic efficiency based on market prices.

Moreover, the state of charge (SoC) constraints on the BESS would be as follows,

$$SoC_{t+1} = SoC_t + \eta_c \left(\frac{x_t^{G2B}}{B^{es}} + \frac{x_t^{P2B}}{B^{es}} \right) - \frac{1}{\eta_d} \frac{x_t^{B2G}}{B^{es}} \tag{28a}$$

$$SoC_t^{min} \le SoC_t \le SoC_t^{max} \tag{28b}$$

$$SoC_1 = SoC_{24} \tag{28c}$$

where, (28a) denotes the SoC change of BESS with time, while (28c) implies that SoC of BESS at day beginning ($t = 1$) equals the SoC at day end ($t = 24$). The variable x_t^{P2B} denotes the energy transfer from the PV to BESS. Therefore, either BESS can charge from the grid or the PV, but not both simultaneously. The constraint is ensured as follows,

$$0 \le x_t^{G2B} \perp x_t^{P2B} \ge 0 \tag{29a}$$

$$0 \le x_t^{G2B} \perp x_t^{B2G} \le 0 \tag{29b}$$

$$0 \le x_t^{P2B} \perp x_t^{B2G} \le 0 \tag{29c}$$

where, (29a) ensures that BESS charges either from PV or the grid, while (29b) and (29c) ensure that BESS is either charging or discharging at any particular time. Moreover, the discharging variable x_t^{B2G} only takes non-positive values.

Remark 2. In this work, the size of the BESS is not predefined. Instead of setting a predetermined size or imposing constraints on it, our model allows the size of the BESS to be determined as an outcome of the optimization process. This is achieved by analysing the optimal charging and discharging patterns over a typical day, which in turn gives required capacity of the BESS for effective energy balancing

Solving, the balancing objective (27) subject to constraints (28)–(29), the LEC can achieve the lowest possible balancing costs for fulfilling the 24/7 PPA contractual obligations. Moreover, an additional on BESS discharging would be placed as follows,

$$\Omega_t \le x_t^{B2G} \tag{30}$$

$$\Omega_t = \begin{cases} 0 & \text{if } x_t^{PPA} \le x_t^{PV} \\ x_t^{NET} & \text{if } x_t^{PV} < x_t^{PPA} \end{cases} \tag{31}$$

which only allows discharging the BESS when PPA contracted power is less than actual PV generation.

As a consequence, surplus PV generation would be allocated towards charging the BESS. Moreover, the utilization of BESS is strictly restricted to serve as a balancing asset within the PPA framework and thus energy arbitrage, i.e., capitalizing on the differences in energy prices at different times, is strictly prohibited. This emphasizes the exclusive role of BESS in maintaining the balance between PV generation and the PPA obligations, rather than as a tool for speculative gains.

In the case day-ahead PV generation forecasts x_t^{PV} are not accurate, a level of uncertainty may be modelled in them as follows [28],

$$\tilde{x}_t^{PV} = x_t^{PV} + \eta \tag{32}$$

where, $\tilde{x}_t^{PV}$ denotes the uncertain PV generation at time t, and $\eta \in [-\hat{x}_t^{PV}, \hat{x}_t^{PV}]$ is a random variable that can vary within a predefined

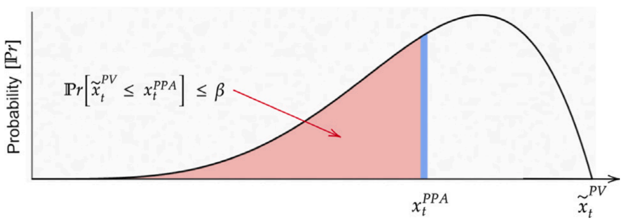

Fig. 4. Uncertainty quantification of PV generation compared to PPA volume.

interval. Subsequently, constraint (31) can be re-modelled as a chance constraint as follows,

$$\mathbb{P}\mathrm{r}[x_t^{NET} \geq 0] \geq \delta \tag{33}$$

where, $\delta \in [0, 1]$ is the probability confidence value. Thus, the constraint of x_t^{NET}, that is, $x_t^{PPA} - \tilde{x}_t^{PV}$ being greater than zero would have to be satisfied with a probability δ, considering stochastic $\tilde{x}_t^{PV}$. However, as also depicted in Fig. 4, uncertain PV generation would be less than the fixed PPA contracted volume with a certain probability β,

$$\mathbb{P}\mathrm{r}[\tilde{x}_t^{PV} \leq x_t^{PPA}] \leq \beta \tag{34}$$

Thus, the choice of risk measure by the LEC operator in (12) would also decide the feasibility of the chance constraint (33). That is, as the contracted PPA volume x_t^{PPA} is chosen such that the cumulative probability β in Fig. 4 greater than δ. This would ensure that the constraint set Ω_t is satisfied even in scenarios of high PV generation thereby allowing the BESS to discharge more throughout the optimization timeline.

3. Case studies

3.1. Parameters for modelling

To study the economic viability of the proposed 24/7 PPA framework, four distinct weather and energy market scenarios (of Austria, Norway, Spain & Netherlands) are undertaken. It is assumed that a PV of size 50 kW is installed at LECs situated in all four countries. The yearly PV generation data is taken from [29], while the day-ahead energy prices are taken from [30]. For each of the four cases, we consider an optimally sized BESS to be available for energy balancing. Moreover, the capacity sizing requirement of BESS is also studied comparative to the country wise dynamics. It is further assumed that local energy consumption of LEC consumers is fixed, thus is not explicitly modelled in this work. Nevertheless, assuming consumer loads to be constant, the proposed methodology in this work can be easily extended to incorporate energy consumption of consumers as well.

The maximum charging and discharging rate of the BESS is assumed to be 0.25 times its capacity rating. Specifically, the BESS can charge or discharge its entire energy capacity in 4 hours. Moreover, the charging and discharging efficiency of BESS is taken to be $\eta^c = \eta^d = 0.95$. The proposed algorithmic framework is modelled in MATLAB R2022b using Yalmip, and solved through Gurobi on a PC with 2.4 GHz CPU and 16 GB of RAM. The day ahead market prices for all the countries are shown in Fig. 5. Moreover, the PV generation profile in all different countries is shown in Fig. 6. It may be noticed that for a fixed size of PV, the capacity utilization factor (CUF) of Spain would be the highest given its year-round sunnier climate.

3.2. Long-term volume prediction and price negotiation

The initial step of the proposed methodology is to predict the long-term PV generation, so as to ascertain the hour-by-hour volume of energy exchange under the PPA contract. Fig. 7 shows the long term prediction of PV generation using LSTM over a particular season. In

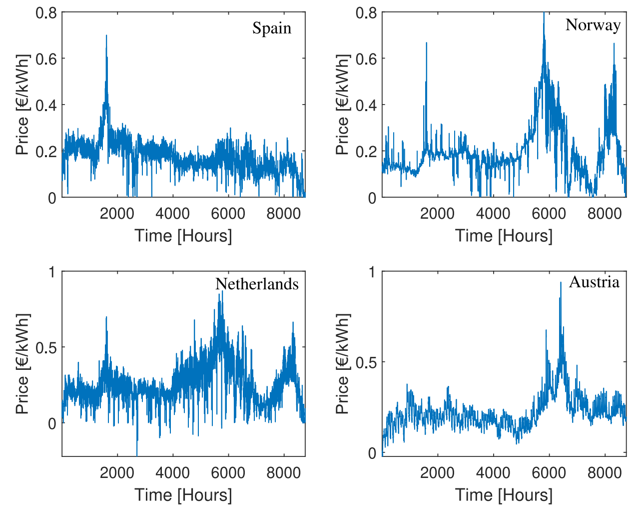

Fig. 5. Day-ahead market price of all countries (Year 2022).

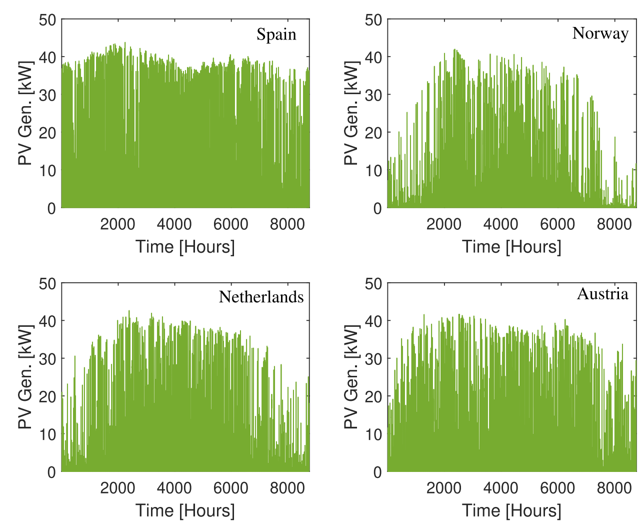

Fig. 6. Variation in PV generation for fixed capacity size of 50 kW.

particular, the PV generation profile of summer month (June) and winter month (December) for Norway are shown. It may be noticed that the summer month in Fig. 7(a) is easier to predict with higher accuracy due to less intermittency in actual PV generation profile. In Fig. 7(a) it is seen that the actual PV production is marginally higher/lower than the prediction for any typical day. Moreover, the predicted profile is seen to capture the cyclic trend and the amplitude of daily maximum PV generation very accurately for many days and hours. Similarly, Fig. 8 shows the prediction of PV generation for the winter months of rest of the countries.

On similar lines, in Fig. 9 the monthly forecasts also portray an accurate prediction of the actual generation of PV. This is also established by seeing Fig. 10 which shows the RMSE while executing the LSTM prediction training. After 200 iterations the RMSE, on training data, is seen to be lower than 0.1. Moreover, a consistent improvement in RMSE is seen with increasing iterations. However, in Fig. 7(b) the PV generation forecast of winter month is shown. It may be noticed that the amplitude of the PV generation is predicted with high accuracy. This is because, the maximum generation forecasted to be around 4 kW on average, coincides with the actual data. However, there are still several days with lower than anticipated PV generation, primarily due to unpredictable weather and low solar irradiation in the winter

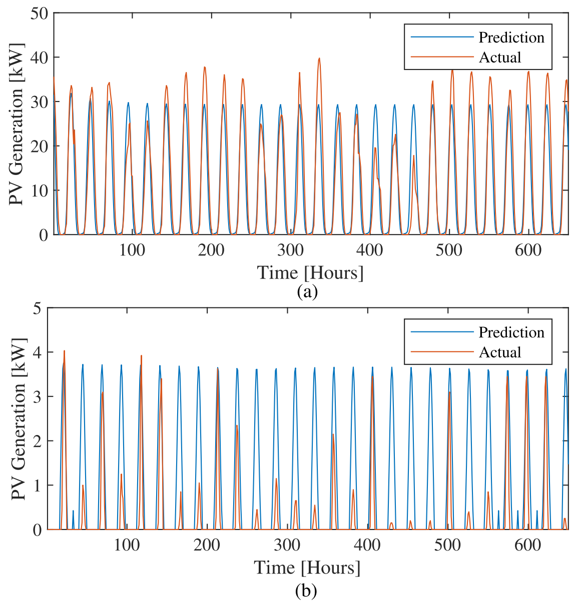

Fig. 7. Long term amplitude and cyclic trend analysis of hourly PV generation for Norway. (a) Month of June (b) Month of December.

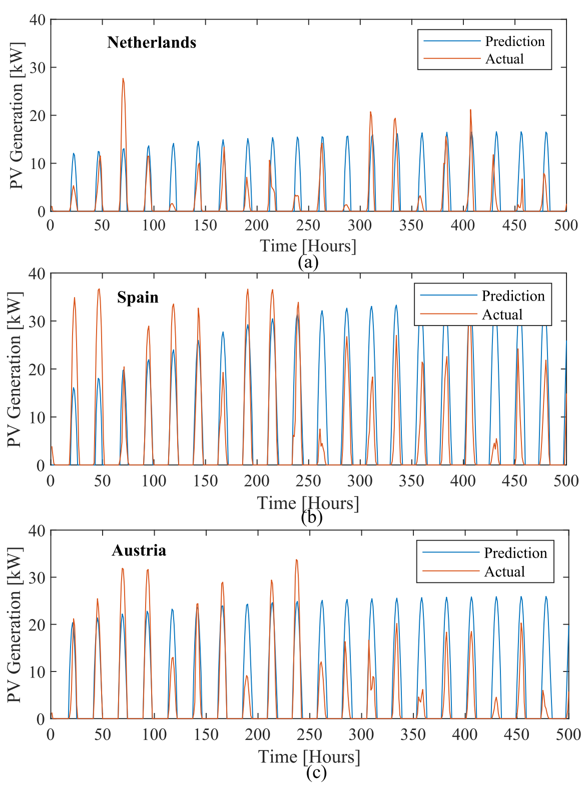

Fig. 8. Hour to hour prediction of solar generation for long-term (monthly) scenario of different countries. Winter month of December.

climate of Norway. These predictions become the primary point for deciding the volumetric energy exchange between the LEC as a seller and the outside buyer. For comparison, Table 1 shows the long-term prediction performance of two additional methods of support vector regression (SVR) and seasonal ARIMA (S-ARIMA). It is evident that LSTM outperforms SVR and S-ARIMA in terms of long-term forecasting accuracy for PV generation, as indicated by its lower RMSE value. Additionally, LSTM's ability in cyclic trend prediction suggests it is

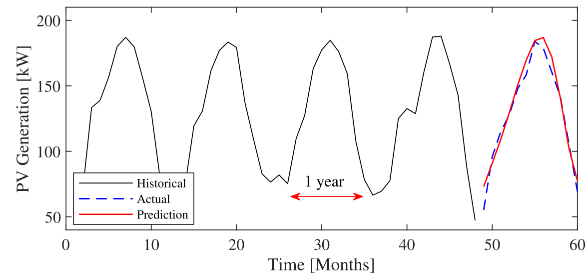

Fig. 9. Long term prediction for a year on a monthly basis.

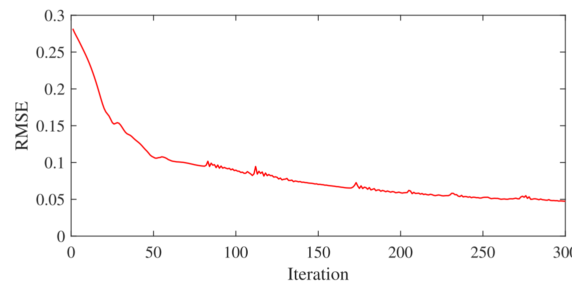

Fig. 10. RMSE of LSTM on training data for hourly PV generation forecast of Norway.

better suited for capturing the patterns in PV output across different seasons and times of the day.

In Fig. 11, VaR measure is used on a typical day of the summer month. The LSTM prediction is shown which is assumed to be maximum PV production of the day. The seller-LEC may however, choose to limit its contracted volume of PV to be sold in the forward 24/7 PPA contract. The computation of the different PV generation profiles for contracting in the PPA are considered based on the confidence intervals decided by the parameter α-VaR. The parameter α shows the seller's risk-tolerance, which would be lower as the parameter increases. For a given value of α, the seller would calculate the probability of PV generation of a typical day to be lower than a threshold value decided using VaR. As the risk tolerance decreases, the PV generation profile also decreases in probabilistic measure. As seen in Fig. 11, with α as 0.9, the PV generation profile for selling in the PPA contract is very low. However, $\alpha = 0.9$ ensures that PV generation would fall below the contracted volume only in worst 10% cases, thereby ensuring low risk and balancing requirements from the seller.

Fig. 12 shows the price of the PPA contract with varying bargaining power between the seller and the buyer. As parameter ϑ increases, the seller gains higher bargaining power, and vice-versa. Thus, the PPA price sees a monotonic increase with increasing ϑ, as the seller is able to bargain a higher price for the long-term contract. However, due to modelling constraints of the disagreements points d_s and d_b within the NBS framework, the strike price remains within the lower limit of LCOE and the predicted wholesale market price τ. The case of equal bargain incorporates the generalized NBS, where $\vartheta = 0.5$, where an fair settlement of the long term price is made. It may be further noted that linear utility functions, of both seller and buyer, allow a linear price-bargaining power relationship. However, for conventional generators with quadratic fuel-cost curves, the NBS would reflect the non-linear relationship, as the bargaining power impacts both the price and volume, due to the inherent convexity of their cost structure.

3.3. Day-ahead energy balancing strategies

Fig. 13 shows the day-ahead prediction of PV generation using AR modelling. Using previous day's generation as the input, we predict the next day (24 h) PV output. This short-term hour-to-hour prediction is

Table 1
Comparative analysis of LSTM, SARIMA, and SVR for long-term PV prediction.

Feature/Model	LSTM	S-ARIMA	SVR
RMSE (on test dataset)	0.09	0.134	0.171
Cyclic Trend Prediction	Excellent	Moderate	Limited
Training Time	23 min	7 min	11 min
Model Complexity	High (many layers, considered black-box)	Low (requires seasonality adjustment)	Low (kernel choice critical)
Data Preprocessing Requirements	Normalization, time-series prep, optimal look-back selection	Stationarity check, time-lag differencing	Scaling, Lagged-input, Normalization

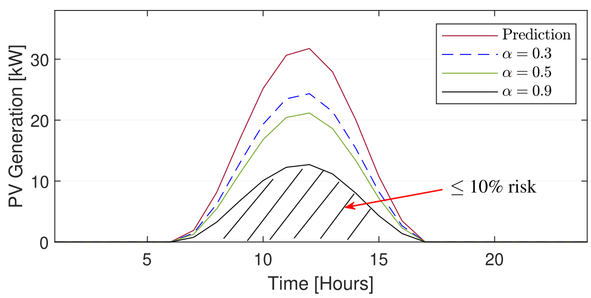

Fig. 11. Volumetric VaR of PV generation profile of a typical day with varying confidence intervals.

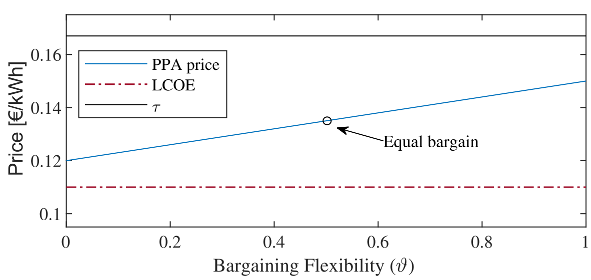

Fig. 12. PPA strike price variation with changing bargaining power (ϑ) of the buyer-seller pair.

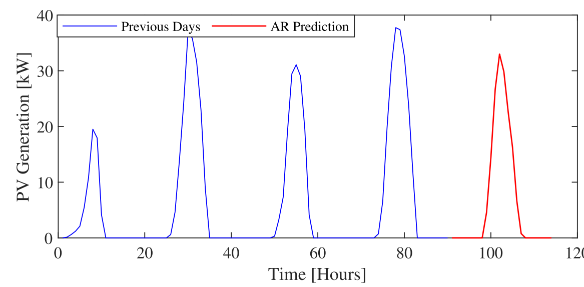

Fig. 13. Day-ahead prediction of PV generation using AR modelling.

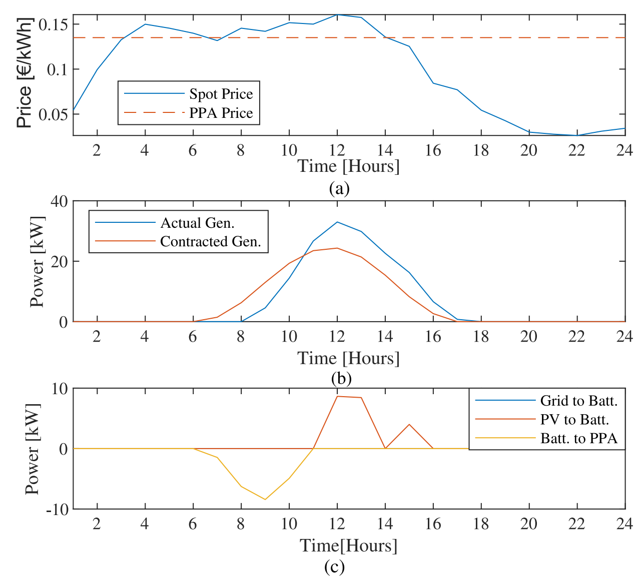

Fig. 14. Balancing requirements in a typical day with PV generation surplus (a) Market and PPA prices. (b) PV generation contracted in PPA and actual PV generation. (c) Charging/discharging requirements from BESS for balancing.

useful in deciding the difference between the contracted and the actual PV generation for the next day. If the prediction is dissimilar to the contracted, the seller might opt for computing an optimal schedule for the BESS providing balancing services. In Fig. 14(b) the balancing requirements can be seen for a day when PV generation is usually higher than contracted. However, it may be noticed that in hour 6 to hour 10, the contracted generation is marginally higher. Thus, there would be balancing requirement in those hours by discharging the BESS. In effect, the deficit in PV generation for the first few hours can be offset easily as seen in Fig. 14(c). Moreover, the required SoC of the BESS is gained back in the following hours through PV to BESS charging. Therefore, using a BESS, the requirement to procure balancing power from the energy market is avoided entirely. That is, neither the seller or the buyer has to procure energy from the real-time market for balancing.

In contrast, Fig. 15 shows the balancing requirements in a typical day with low PV generation, i.e. generation deficit at all hours. It is evident that energy has to bought from the market to cover the unavailability of PV generation. In Fig. 15(b), during hour 20 to hour 24, when the spot price falls below the PPA price, the battery system is effectively charged from the grid. PV to battery is zero as this is a deficit example case where predicted generation is less than contracted generation. The BESS, however, plays a crucial role by discharging its stored energy to fulfil the contracted power requirements for the buyer with whom there is a PPA. This enables the delivery of the agreed-upon power despite the deficit in PV generation, ensuring contractual obligations are met. The optimal BESS size in this case comes out to be 50 kWh, which signifies the need for larger storage systems when the PV generator of the LEC under-produces power.

Fig. 16 provides an overview of the costs and benefits associated with a sustainable LECs. The costs labelled as “Grid import costs” represent the expenses incurred when purchasing power from the grid in the event of a power deficit. “Revenue from the market” indicates the income generated by selling excess power to the open market. “Revenue from the PPA” represents the earnings obtained from selling power to a specific buyer with whom the seller-community has a PPA contract. The “Overall revenue” refers to the profit obtained by subtracting the grid import costs from the revenue generated in the market. In the absence of a BESS, the seller must purchase power from the grid to meet the contracted power requirements when the predicted generation falls short. Conversely, the implementation of a

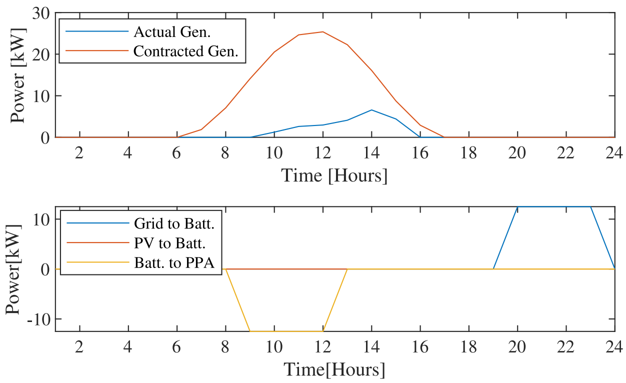

Fig. 15. Balancing requirements in a typical day with PV generation deficit (a) PV generation contracted in PPA and actual PV generation. (b) Charging/discharging requirements from BESS for balancing.

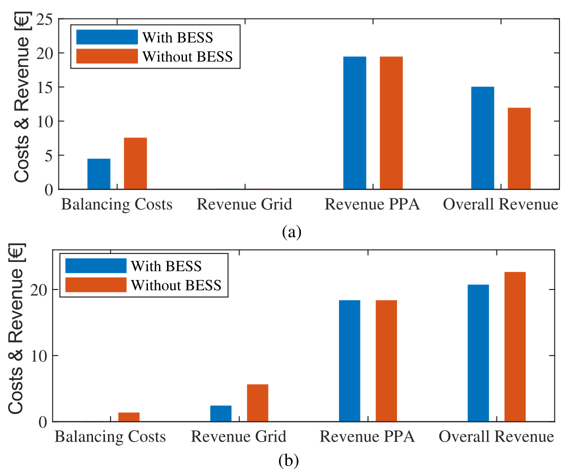

Fig. 16. Balancing costs and PPA revenue of a typical day (a) Surplus day (b) Deficit day.

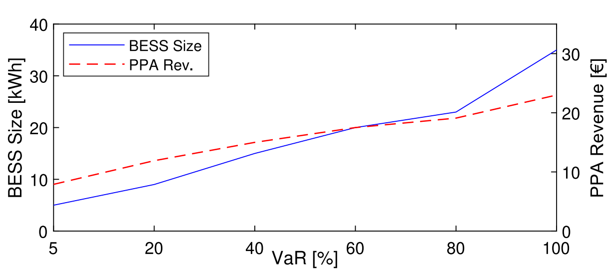

Fig. 17. Variation in PPA revenue and BESS capacity as a function of evolving VaR.

BESS enables the community to reduce its reliance on the grid to fulfil the contract, thereby diminishing the need for grid imports and eliminating grid import costs. It is essential to acknowledge that in the absence of BESS, having surplus power can be advantageous. If the spot price at a particular exceeds the PPA price, the community can generate income by selling the excess power to the grid. Therefore, the revenue earned from selling to the market, without BESS, surpasses the revenue earned with BESS.

Fig. 17 illustrates the relationship between PPA revenue for a standard day and BESS size based on changing risk assessments in PV generation included in the PPA. At a 5% VaR, the PV generation for sale bears a 5% risk, resulting in a modest PPA revenue of €10 daily due to the low contracted volume of PV. This reduced volume also corresponds to a reduced battery capacity need for balancing, making a 6 kWh BESS

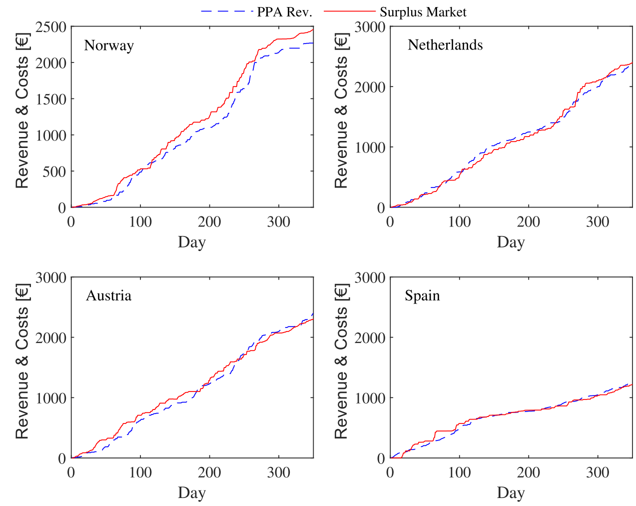

Fig. 18. Country-wise balancing costs and market based revenue for surplus/deficit days.

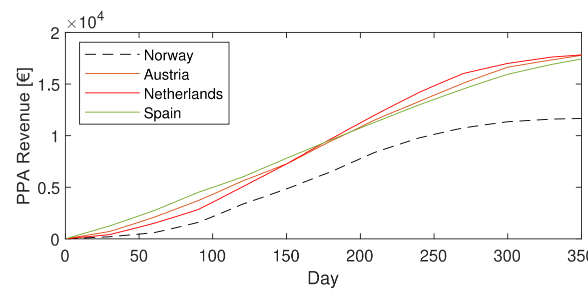

Fig. 19. Country-wise overall PPA revenue for a cumulative year.

adequate. As the contracted PV volume in the PPA grows, both PPA revenue and BESS size proportionally increase. It may be noted that the BESS size growth rate exceeds that of the PPA revenue, indicating that the challenges in balancing unpredictable PV generation surpass the PPA contract's revenue benefits.

3.4. Effect of climatic conditions and market dynamics on PPA feasibility

This section explores the factors that contribute to the unique characteristics and circumstances of different climatic and market dynamics, resulting in differences in the arrangements of PPA profitability. The differences in PPA arrangements for photovoltaic (PV) systems among different countries can be attributed to several factors. Some of the key factors include variations in spot prices, and variations in PV generation profiles.

Fig. 18 shows the costs associated with balancing deficits, i.e. purchasing from, and surpluses, i.e. selling to the energy market. It may be seen that Spain incurs lower costs compared to other countries, indicating a closer alignment with contracted PV production, and low uncertainty of PV production with high CUF. However, the situation in Norway is different. Throughout the year, the cost of balancing deficits is consistently higher than the revenue generated from surplus power. This pattern indicates a significant challenge for higher uncertainty in PV production, especially in the winter months, as was also seen under the long-term prediction mechanism. Finally, Fig. 19 displays the overall profit in different countries, calculated as the summation of PPA revenue and surplus market revenue minus the balancing costs required from the market. For this particular case, we assume the exclusion of an BESS to study the adverse impact of market based balancing costs on the overall PPA profits. Excluding Norway, all countries demonstrate similar profit levels, assuming the same PV production capacity of 50 kW. This disparity underscores the unique challenges faced in achieving profitable PV production under a PPA for particular market dynamics and weather dependent CUF.

4. Conclusions

This paper demonstrated the development of a novel framework for continuous 24/7 PPA contracts with an hourly renewable energy delivery timeline. The framework was designed with the aim of enhancing the economic viability of LECs and increasing returns for its stakeholders. Using advanced statistical prediction tools including LSTM and AR modelling, the proposed framework effectively managed the hour-to-hour power delivery commitments. Moreover, the work demonstrated the utility of cooperative bargaining between seller-buyer pair for negotiating a fixed PPA price, achieving a balanced outcome that ensures pareto optimality of the seller-buyer economic utilities. Furthermore, it is found that integration of a BESS within a 24/7 PPA is effective in managing excess power and bridging supply–demand gaps during low PV generation periods. Significantly, the implemented PPA model demonstrated distinct ability to mitigate long-term price risk tied to day-ahead/wholesale energy markets. The framework's efficiency was validated through several simulation results derived from various climatic conditions and energy market dynamics. The study indicates that the proposed PPA, supplemented with statistical learning methods for risk assessment, has significant potential to minimize financial risks for LECs. The proposed VaR methodology has its limitations in capturing inter-hour dependencies of PV generation, which could potentially impact the risk profile. To address this, the exploration of time-correlated uncertainty models can be considered as a scope of future research to investigate the impact of incorporating time-correlation on the risk assessment for PV generation in the context of 24/7 PPAs.

CRediT authorship contribution statement

Bakul Kandpal: Writing – original draft, Software, Methodology, Conceptualization. **Stian Backe:** Writing – review & editing, Methodology, Conceptualization. **Pedro Crespo del Granado:** Writing – review & editing, Validation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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