Effectively Dispatchable Solar Power with Hierarchical Reconciliation and Firm Forecasting

Dazhi Yang, Guoming Yang, Marc J. Perez, and Richard Perez

Abstract—**The variable nature of solar power has hitherto been regarded as a major barrier preventing large-scale high-penetration solar energy into the power grid. Based on decades of research, particularly those advances made over the recent few years, it is now believed that dispatchable solar power is no longer a conception but will soon become techno-economically feasible. The policy-driven information exchange among the weather centers, grid operators, and photovoltaic plant owners is the key to realizing dispatchable solar power. In this paper, a five-step forecasting framework for enabling dispatchable solar power is introduced. Among the five steps, the first three, namely numerical weather prediction (NWP), forecast post-processing, and irradiance-to-power conversion, have long been familiar to most. The last two steps, namely hierarchical reconciliation and firm forecasting, are quite recent conceptions, which have yet to raise widespread awareness. The proposed framework is demonstrated through a case study on achieving effectively dispatchable solar power generation at plant and substation levels.**

Index Terms—**Hierarchical reconciliation, firm forecasting, solar power, battery storage.**

I. Introduction

FORECASTING plays a major role during the integration of solar power, in particular, photovoltaic (PV) power. However, despite decades of research, the current accuracy level of solar power forecasting is still far from being comparable to that of load forecasting [1]. Since typical solar forecast errors far exceed the amount that can be absorbed by the power grid [2], it is a consensus to regard solar power as non-dispatchable, contrasting the on-demand power from thermal generators or hydropower plants. Fortunately, many innovations have been proposed over the years to reduce solar forecast errors. These technologies are referred to as firm forecast enablers, for they seek to firm up the uncertain solar forecasts. It should be highlighted at this stage that there have been numerous attempts for smoothing out PV power fluctuations with energy storage, but firm forecasting is essentially a new idea, for it involves the joint optimization of several firm forecast enablers, especially the overbuilding and proactive curtailment (see below), which goes beyond using storage alone. It must be highlighted that the traditional view on solar energy utilization favorites ways to lower the curtailment as much as possible; however, firm forecasting is advocating that one should proactively curtail some overbuilt PV power during under-forecasting situations, which appears as a form of energy waste but in fact enhances the overall energy economics [3].

Indeed, according to the recent surveys in [4] and [5], firm forecast enablers can be collected into four categories: ① storage, ② generation smoothing, ③ demand-side management, and ④ overbuilding and proactive curtailment. Storage seeks to store the excess energy when the actual solar generation is higher than the forecast, and release the stored energy when there is a deficit in generation [6], [7]. Generation smoothing aims at combining geographically dispersed or complimentary generation sources, such that the fluctuations on different scales can be canceled out to a certain extent for achieving a smoother generation profile that is easier to forecast [8]. Demand-side management generally refers to load shaping through scheduling and shifting the electricity usage according to the solar forecast profile. Last but not least, overbuilding and proactive curtailment, which is a rather recent idea first formalized in [9], takes advantage of the rapid price drop of PV system and deliberately expands its capacity, such that some of the over-forecasts can be mitigated by the generation from the overbuilt part. This technology is therefore also known as implicit storage [10]. In principle, all four categories of firm forecast enablers modify the generation, forecast, or both profiles, to facilitate the matching of the two profiles on all spatio-temporal scales that are relevant to grid integration. It should be understood a priori that no single enabler is able to achieve firm forecasting on its own, insofar as energy economics is to be factored in at any rate. Instead, one looks for an optimal combination of the four categories.

Regardless, firm forecast enablers have to work in line with the current grid integration policies. As such, the current solar forecasting practices are first reviewed in Section

Manuscript received: April 29, 2024; revised: July 8, 2024; accepted: October 12, 2024. Date of CrossCheck: October 12, 2024. Date of online publication: November 7, 2024.

This work was supported in part by the National Natural Science Foundation of China (No. 42375192) and the China Meteorological Administration Climate Change Special Program (No. QBZ202315).

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DOI: 10.35833/MPCE.2024.000451

II-A. In a nutshell, the current forecasting practices are often associated with a two-way information flow, where national agencies issue weather forecasts to plant owners, who are responsible for post-processing and converting them to PV power forecasts, and submitting the PV power forecasts to the grid operators [11]. It is argued in this paper that this information flow is insufficient. Instead, the grid operators should revise the forecasts they receive and send the reconciled forecasts back to the plant owners, such that the plant owners can leverage various firm forecast enablers to match their own generation targets. In this way, solar power becomes effectively dispatchable [12]. The methods to reconcile forecasts and to firm them up are detailed in Sections II-B and II-C, respectively. This combination of hierarchical reconciliation and firm forecasting is innovatively proposed in this paper. Section III demonstrates the validity of the proposed framework with a case study. The economics of dispatchable solar power is made clear. The benefits of storage sharing (both explicit, i. e., batteries, and implicit, i. e., PV overbuilding) are quantified. The findings suggest that firming up substation-level forecasts is more sensible than firming up individual-plant forecasts. With the state-of-the-art forecast reconciliation and the current market prices of PV and battery, one only has to invest an additional 95 \$/kW to achieve effectively dispatchable solar power in California, USA.

II. Five-step Forecasting Framework

A. Current Solar Forecasting Practices

Insofar as solar forecasting for grid integration is concerned, there are two go-to methods, namely satellite-based forecasting and numerical weather prediction (NWP), with the former supporting intra-day forecasting and the latter supporting day-ahead forecasting [1]. Note that time-series forecasting can rarely generate meaningful forecasts for individual PV plants; however, it can be useful in other circumstances where the power output of multiple PV plants is aggregated and smoothed. Both methods can issue irradiance forecasts over wide geographical areas with decent accuracies. Satellite- and NWP-based forecasts are usually generated by national and intergovernmental weather centers, for the techniques involved are intricate and mandate real-time flow of big data. For instance, the WSP-based model of China Meteorological Administration is specifically aligned to the grid code of China, catering to various wind and solar forecasting needs [13]. Therefore, it is the first step toward dispatchable solar power to have irradiance forecasts issued by weather centers. This step is already operational in many countries worldwide.

That said, even forecasts from the best satellite- and NWP-based models are found to be biased and under-dispersed, due to our incomplete understanding of various atmospheric processes and lack of timely observations for data assimilation [14], [15]. More importantly, predicting motions on unresolved scales, such as those of clouds, is outright impossible with the current technology and over a very long foreseeable future. Post-processing, which is able to downscale [16] and improve [17] the initial forecasts, is therefore necessary. which is the second step. The post-processing of irradiance forecasts has been thoroughly reviewed in [18] and thus is not reiterated here. Worth mentioning however is that post-processing requires ground-based observations. As such, this step is usually performed by plant owners or forecast service providers, who often possess data from radiometers that collocate with the PV plants.

The third step involves converting the post-processed irradiance forecasts to PV power, which is commonly done via a model chain, or more formally, a solar power curve [19]. A model chain uses a series of solar energy meteorology models in cascade, where the output of a preceding model is used as the input of a succeeding model, forming a chain-like structure echoing its name. There has been a recent wave of investigation to contrast the various deterministic and probabilistic methods for constructing model chains [20]-[23]. The performance of a model chain depends largely on the availability of plant design parameters, such as the panel orientation, array configuration, or inverter sizing. Since such information is not managed in a centralized way but possessed by individual plant owners, they should be responsible for this irradiance-to-power conversion step.

The three-step PV power forecasting framework, first of NWP, second of post-processing, and third of irradiance-to-power conversion, is familiar to many, and is generally regarded as the most promising and advanced one to date [24], [25]. At the end of this procedure, as many grid operators around the world mandate, the plant-level forecasts are to be submitted to balancing authorities, who then use the forecasts for power system operations of various sorts. This concludes the current status quo on interactions among weather centers, grid operators, and individual plant owners. However, two questions remain. ① What is the best way to aggregate the plant-level forecasts to substation or load zone levels, on which the balancing is commonly conducted? ② As the penetration level continues to elevate, how to mitigate the uncertainty caused by inaccurate forecasts, which may disturb the distribution and transmission networks? The answers to these questions are provided next.

B. Hierarchical Forecast Reconciliation

Many time series in social and physical settings, including the PV generation time series, can be framed into hierarchical structures. More specifically, the plant-level PV generation can be gathered according to distribution feeder nodes, balancing authority areas, load zones, or substations of different voltage levels. To give perspective, Fig. 1 shows the locations and sizes of 405 simulated PV plants (the data are more described below), 115-345 kV transmission lines, and 500 kV lines/substations in California, USA. The PV plants can be aggregated and thus managed according to such a configuration. Nevertheless, inasmuch as the forecasts are to be generated for all levels of the hierarchy, a problem known as aggregation inconsistency arises.

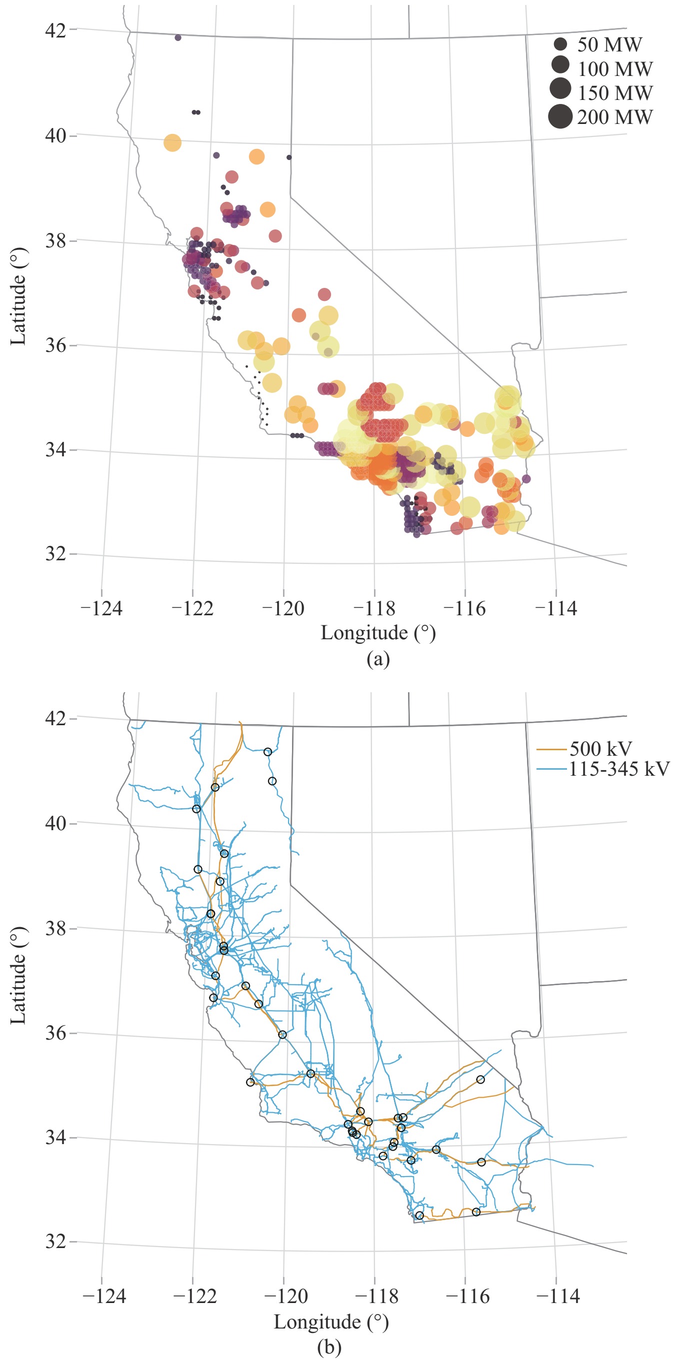

Fig. 1. Locations and sizes of 405 simulated PV plants, 115-345 kV transmission lines, and 500 kV lines/substations in California, USA. (a) PV plants where colors are simply a visual aid to help distinguish overlapped dots. (b) High-voltage transmission lines and substations.

Whereas the actual measurements across a hierarchy sum up naturally, the forecasts do not, owing to the modeling uncertainty and information asymmetry. In a solar forecasting context, upper-level forecasts are usually produced by grid operators by extrapolating the aggregated historical generation time series outwards, whereas lower-level forecasts are produced, for example, with the aforementioned three-step framework. It would be very difficult to imagine that the lower-level forecasts, against all odds, sum up exactly to the higher-level ones, unless very naive methods such as persistence is used. On this point, hierarchical forecasting seeks to produce a set of aggregate consistent forecasts across the hierarchy, facilitating joint decision-making. Besides that, forecast reconciliation brings to the table several other benefits, such as accuracy improvements [26] or feasibility for operating on large time series [27], which are desirable in a grid integration context. Most importantly, reconciliation does not place any requirement on the base forecasting methods that can generate forecasts [28], as such when the base forecasting methods evolve, the reconciliation model is able to accommodate any update fairly easily. This property is also useful in situations where low-quality and missing data affect the plant-level forecasts, in that the forecasts may be solicited through another method.

For deterministic forecast reconciliation, one of the best methods is known as the optimal reconciliation technique, which is able to minimize the reconciliation errors in the least-squares sense. Originally proposed in [29], the optimal reconciliation technique has evolved several times [27], [28]. Whereas the mathematical proofs can be found in [27] and [28], this paper only outlines the basic mathematical setup of the optimal reconciliation technique.

Denoting observation (i.e., PV power measurement) by y, one can collect all observations made at time t into a vector $\boldsymbol{y}_t$:

$$\boldsymbol{y}_t = \left[y_{0,t}, \boldsymbol{y}_{1,t}^{\mathrm{T}}, \boldsymbol{y}_{2,t}^{\mathrm{T}}, \ldots, \boldsymbol{y}_{b,t}^{\mathrm{T}} \right]^{\mathrm{T}} \tag{1}$$

where $y_{0,t}$ is the total PV power measured in the power system; and $\boldsymbol{y}_{1,t}, \boldsymbol{y}_{2,t}, \ldots, \boldsymbol{y}_{b,t}$ are the vectors of measurements corresponding to different levels of the hierarchy, with b denoting the bottom level. According to the hierarchical nature,

$$\boldsymbol{y}_t = \boldsymbol{S}\boldsymbol{y}_{b,t} \tag{2}$$

where $\boldsymbol{S}$ is a summing matrix. That said, $\boldsymbol{y}_t$ can be constructed by the bottom-level measurements and $\boldsymbol{S}$, which contains only zeros and ones. To give perspective on the notation, a two-level hierarchy is used as an example in Supplementary Material A.

Similar to observation, the forecast is denoted by x or $\boldsymbol{x}$, and one may collect forecasts across the hierarchy at time $t+h$ into a vector $\boldsymbol{x}_{t+h}$:

$$\boldsymbol{x}_{t+h} = \left[x_{0,t+h}, \boldsymbol{x}_{1,t+h}^{\mathrm{T}}, \boldsymbol{x}_{2,t+h}^{\mathrm{T}}, \ldots, \boldsymbol{x}_{b,t+h}^{\mathrm{T}} \right]^{\mathrm{T}} \tag{3}$$

Aggregation inconsistency suggests:

$$\boldsymbol{x}_{t+h} \neq \boldsymbol{S}\boldsymbol{x}_{b,t+h} \tag{4}$$

Denoting the reconciled version of forecasts by adding a tilde to the relevant expression, a set of aggregate consistent forecasts may be written as $\tilde{\boldsymbol{x}}_{t+h}$:

$$\tilde{\boldsymbol{x}}_{t+h} = \boldsymbol{S}\tilde{\boldsymbol{x}}_{b,t+h} \tag{5}$$

In this regard, the goal of reconciliation is to find an optimal choice of matrix $\boldsymbol{P}$ such that:

$$\tilde{\boldsymbol{x}}_{t+h} = \boldsymbol{S}\boldsymbol{P}\boldsymbol{x}_{t+h} \tag{6}$$

$\boldsymbol{x}_{t+h}$, as in (3), is the vector of forecasts before reconciliation, which is otherwise known as the (incoherent) base forecast.

Numerous methods exist for obtaining $\boldsymbol{P}$. For instance, in the bottom-up (BU) method, which assumes that the higher-level forecasts are simply obtained by summing up lower-level ones, the matrix $\boldsymbol{P}$ becomes $\boldsymbol{P}^{\text{BU}}$:

$$\boldsymbol{P}^{\text{BU}}=\left(\boldsymbol{O}_{m_b\times(m-m_b)}\middle|\boldsymbol{I}_{m_b}\right) \tag{7}$$

where m is the total number of series in the hierarchy; m_b is the number of bottom-level series in the hierarchy; $\boldsymbol{I}_{m_b}$ is an identity matrix with the size of m_b; and $\boldsymbol{O}_{m_b\times(m-m_b)}$ is an $m_b\times(m-m_b)$ matrix of zeros. Moving beyond the trivial BU reconciliation, the common problem-solving philosophy of statisticians is to find a choice of $\boldsymbol{P}$ such that it minimizes some loss functions. On this point, the generalized least squares (GLS) reconciliation, which minimizes the reconciliation error $\boldsymbol{\varepsilon}_h$ in the least squares sense, becomes a natural choice.

$$\boldsymbol{\varepsilon}_h=\boldsymbol{x}_{t+h}-\boldsymbol{S}\boldsymbol{\beta}_{t+h} \tag{8}$$

$$\boldsymbol{\beta}_{t+h}=\mathbb{E}\left(\boldsymbol{y}_{b,t+h}\middle|\boldsymbol{y}_1,\boldsymbol{y}_2,\dots,\boldsymbol{y}_t\right) \tag{9}$$

$\boldsymbol{\beta}_{t+h}$ is the conditional expectation of the bottom-level observation random vector at $t+h$ given previous observations up to time t, i.e., $\boldsymbol{y}_1,\boldsymbol{y}_2,\dots,\boldsymbol{y}_t$. This idea of GLS reconciliation was first given in [30], and later modified in [28]. As the detailed derivation can be found in the original papers, one should note that matrix $\boldsymbol{P}$ under GLS reconciliation takes the form of $\boldsymbol{P}^{\text{GLS}}$ given as:

$$\boldsymbol{P}^{\text{GLS}}=\left(\boldsymbol{S}^{\text{T}}\boldsymbol{\Sigma}_h^{\dagger}\boldsymbol{S}\right)^{-1}\boldsymbol{S}^{\text{T}}\boldsymbol{\Sigma}_h^{\dagger} \tag{10}$$

where $\boldsymbol{\Sigma}_h$ is the variance-covariance matrix of the h-step-ahead reconciliation error $\boldsymbol{\varepsilon}_h$, and $\boldsymbol{\Sigma}_h^{\dagger}$ is its Moore-Penrose generalized inverse. Consequently, substituting (10) into (6) yields (10), where $\tilde{\boldsymbol{x}}_{t+h}$ under GLS reconciliation takes the form of $\tilde{\boldsymbol{x}}_{t+h}^{\text{GLS}}$ given as:

$$\tilde{\boldsymbol{x}}_{t+h}^{\text{GLS}}=\boldsymbol{S}\left(\boldsymbol{S}^{\text{T}}\boldsymbol{\Sigma}_h^{\dagger}\boldsymbol{S}\right)^{-1}\boldsymbol{S}^{\text{T}}\boldsymbol{\Sigma}_h^{\dagger}\boldsymbol{x}_{t+h} \tag{11}$$

$\boldsymbol{\Sigma}_h$ is unknown and can be hard to estimate, and thus alternative methods are needed. On this account, the so-called minimum-trace (MinT) reconciliation proposed in [28] is used, as shown in (12), where $\boldsymbol{P}$ under MinT reconciliation takes the form of $\boldsymbol{P}^{\text{MinT}}$ given as:

$$\boldsymbol{P}^{\text{MinT}}=\left(\boldsymbol{S}^{\text{T}}\boldsymbol{W}_h^{-1}\boldsymbol{S}\right)^{-1}\boldsymbol{S}^{\text{T}}\boldsymbol{W}_h^{-1} \tag{12}$$

where $\boldsymbol{W}_h$ is the variance-covariance matrix of base forecast error $\boldsymbol{e}_{t+h}$:

$$\boldsymbol{e}_{t+h}=\boldsymbol{y}_{t+h}-\boldsymbol{x}_{t+h} \tag{13}$$

As such, the reconciled forecasts can be obtained from:

$$\tilde{\boldsymbol{x}}_{t+h}^{\text{MinT}}=\boldsymbol{S}\left(\boldsymbol{S}^{\text{T}}\boldsymbol{W}_h^{-1}\boldsymbol{S}\right)^{-1}\boldsymbol{S}^{\text{T}}\boldsymbol{W}_h^{-1}\boldsymbol{x}_{t+h} \tag{14}$$

where $\tilde{\boldsymbol{x}}_{t+h}^{\text{MinT}}$ denotes $\tilde{\boldsymbol{x}}_{t+h}$ under MinT reconciliation.

It should be noted that the MinT reconciliation minimizes the trace of the variance-covariance matrix of the reconciled forecast error:

$$\tilde{\boldsymbol{e}}_{t+h}=\boldsymbol{y}_{t+h}-\tilde{\boldsymbol{x}}_{t+h} \tag{15}$$

However, it only leverages the variance-covariance matrix of base forecast error, which can be seen in (13); this has been the foremost significance. To estimate $\boldsymbol{W}_h$, one has to shrink the entries of the n-sample estimates of the variance-covariance matrix of the one-step-ahead forecast errors toward its diagonal:

$$\hat{\boldsymbol{W}}_{1,D}^{*}=\lambda_D\hat{\boldsymbol{W}}_{1,D}+\left(1-\lambda_D\right)\hat{\boldsymbol{W}}_1 \tag{16}$$

$$\hat{\boldsymbol{W}}_1=\frac{1}{t}\sum_{i=1}^{t}\boldsymbol{e}_i\boldsymbol{e}_i^{\text{T}} \tag{17}$$

where $\hat{\boldsymbol{W}}_{1,D}^{*}$ is the new version of $\boldsymbol{W}_h$; $\boldsymbol{e}_i$ is the base forecast error; $\hat{\boldsymbol{W}}_1$ is the in-sample estimate of the variance-covariance matrix of the one-step-ahead base forecast errors; $\hat{\boldsymbol{W}}_{1,D}=\text{diag}\left(\hat{\boldsymbol{W}}_1\right)$ is the diagonal matrix of $\hat{\boldsymbol{W}}_1$; and λ_D is a shrinkage parameter, which can be computed using the method of [31]. Then, given any base forecast $\boldsymbol{x}_{t+h}$, the MinT-shrink-reconciled forecast $\tilde{\boldsymbol{x}}_{t+h}^{\text{MinT-shrink}}$ is:

$$\tilde{\boldsymbol{x}}_{t+h}^{\text{MinT-shrink}}=\boldsymbol{S}\left(\boldsymbol{S}^{\text{T}}\left(\hat{\boldsymbol{W}}_{1,D}^{*}\right)^{-1}\boldsymbol{S}\right)^{-1}\boldsymbol{S}^{\text{T}}\left(\hat{\boldsymbol{W}}_{1,D}^{*}\right)^{-1}\boldsymbol{x}_{t+h} \tag{18}$$

This completes the optimal hierarchical reconciliation step.

Recall that the current grid integration adopts a two-way information flow, in that NWP-based forecasts are disseminated from the weather centers, and individual plant owners submit their converted power forecasts to grid operators [32]. With hierarchical reconciliation, another round of information flow is necessary between grid operators and plant owners. Since reconciliation is able to maximize the utility of both the grid operators and PV plant owners, while the grid operators enjoy the granular lower-level data, which is mandated by policy, they should feedback on courtesy the reconciled forecasts to plant owners, such that the penalty incurred on plant owners could be reduced. This would be how the value of reconciliation materializes under the current remuneration framework. There is a deeper implication of reconciliation, however, if another step is taken. That is, by disseminating the reconciled forecasts, those forecasts can be regarded as a generation target for plant owners, who are tasked to firmly meet the target. Stated differently, if every PV plant owner can guarantee to produce the generation target (i.e., the reconciled forecast) assigned to them, the solar power becomes effectively dispatchable, i.e., whatever being forecast is being generated.

C. Firm Forecasting

To firmly meet the generation target (i.e., reconciled forecasts), one seeks to find an optimal mix of firm forecast enablers that is most economic. As geographical smoothing is passive, firm forecasting in this paper is modeled with two enablers, namely battery storage as well as overbuilding and proactive curtailment, without loss of generality. The logic flow is shown in Fig. 2. Two separate paths (left and right parts of Fig. 2) are available, which correspond to under- and over-forecast situations, respectively. When the forecast is smaller than the actual generation, a part of the actual generation is taken and stored, such that the remaining portion equals the forecast value. When the forecast is greater than the actual generation, the forecast value is jointly fulfilled by solar and battery.

The objective function for the optimization problem is the firm forecast premium, which is denoted as π and defined as the ratio between the levelized cost of electricity (LCOE) of firm forecasting and that of unconstrained PV:

$$\pi=LCOE_{\text{F}}/LCOE_{\text{U}} \tag{19}$$

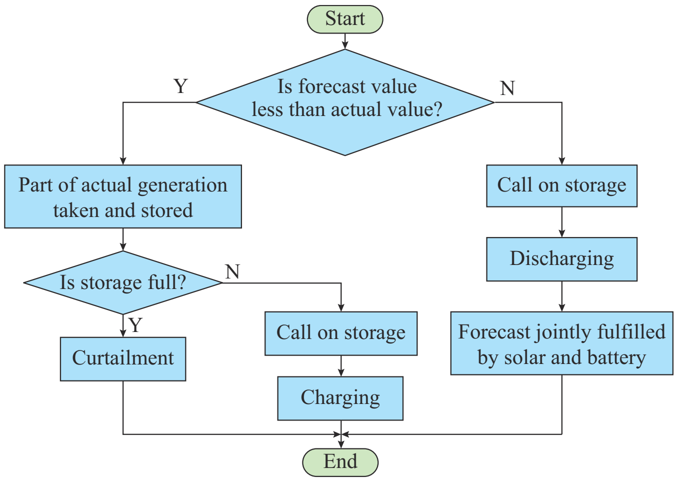

Fig. 2. Logic flow of dynamic curtailing strategy.

where $LCOE_{\mathrm{F}}$ denotes the LCOE of firm forecasting; and $LCOE_{\mathrm{U}}$ denotes the LOCE of unconstrained PV. LCOE is calculated as the ratio of the equivalent annual cost of a generation option over the equivalent annual electrical energy produced by that option. As such, $LCOE_{\mathrm{F}}$ can be written as the ratio of the equivalent annual cost of firm forecasting and annual PV forecast, whereas $LCOE_{\mathrm{U}}$ can be written as the ratio of the equivalent annual cost of unconstrained PV and annual electricity produced by unconstrained PV. The term "unconstrained PV" refers to the as-available (i.e., intermittent) PV installation [9]. For some given reconciled forecast and PV generation profiles, the annual PV forecast and the annual electricity produced by unconstrained PV can be obtained by aggregating the two profiles temporally. Furthermore, the cost of unconstrained PV is also known, e.g., from news reports or energy statistics websites [33], [34]. Therefore, minimizing the firm forecast premium is equivalent to minimizing the equivalent annual cost of firm forecasting.

The equivalent annual cost of firm forecasting comprises four parts: the investment cost of PV, the operation and maintenance (O&M) cost of PV, the investment cost of battery storage, and the O&M cost of battery storage. Mathematically, one can write the equivalent annual cost as:

$$\underset{S_b, \chi, P_{\mathrm{ch},t}}{\arg\min} \left\{ \left(\xi_s + \zeta_s\right) c_s \chi P_s + \left(\xi_b + \zeta_b \sum_{t=1}^{8760} \frac{P_{\mathrm{ch},t}}{S_b}\right) c_b S_b \right\} \tag{20}$$

where ξ_s and ξ_b are the capital recovery factors of solar and battery, respectively; ζ_s and ζ_b are the O&M cost factors of solar and battery, respectively; c_s and c_b are the investment costs, which is in \$/kW for PV and \$/kWh for battery, respectively; P_s is the rated power of unconstrained PV; S_b is the rated capacity of the battery; χ is the overbuilding ratio of the PV; $P_{\mathrm{ch},t}$ is the charging power of the battery at time t, which differs from hour to hour. ξ_s, ξ_b, ζ_s, ζ_b, c_s, c_b, and P_s are known; while S_b, χ, and $P_{\mathrm{ch},t}$ are to be determined by optimization. The capital recovery factors take the well-known form:

$$\begin{cases} \xi_s = r\left(1+r\right)^{l_s} \Big/ \left[\left(1+r\right)^{l_s} - 1\right] \\ \xi_b = r\left(1+r\right)^{l_b} \Big/ \left[\left(1+r\right)^{l_b} - 1\right] \end{cases} \tag{21}$$

where l_s and l_b are the lifetime of solar and battery, respectively; and r is the discount rate.

The minimization problem in (20) must be subject to a series of constraints pertaining to the forecasts, operations of PV, and operations of battery.

PV power forecast made at time t $P_{\mathrm{fcst},t}$ must be fulfilled by grid-injecting PV power at time t $P_{\mathrm{grid},t}$ and (if any) the discharging power at time t $P_{\mathrm{dis},t}$:

$$P_{\mathrm{fcst},t} = P_{\mathrm{grid},t} + P_{\mathrm{dis},t} \tag{23}$$

The power output of PV at any time t $P_{\mathrm{PV},t}$ must be injected into the grid, curtailed (if needed, denoted by $P_{\mathrm{curt},t}$), and/or fed into the battery storage (if needed, denoted by $P_{\mathrm{ch},t}$):

$$P_{\mathrm{PV},t} = P_{\mathrm{grid},t} + P_{\mathrm{curt},t} + P_{\mathrm{ch},t} \tag{24}$$

If the battery is charged or discharged, the charging/discharging power must be within the limits:

$$\begin{cases} 0 \le P_{\mathrm{ch},t} \le B_{\mathrm{ch},t} P_{\mathrm{ch,max}} \\ 0 \le P_{\mathrm{dis},t} \le B_{\mathrm{dis},t} P_{\mathrm{dis,max}} \end{cases} \tag{25}$$

where $P_{\mathrm{ch,max}}$ and $P_{\mathrm{dis,max}}$ are the maximum charging and discharging power of the battery, respectively; and $B_{\mathrm{ch},t}$ and $B_{\mathrm{dis},t}$ are the binary variables representing the charging and discharging states of the battery, respectively, which must satisfy (27), assuming that the battery cannot be charged and discharged at the same time.

$$B_{\mathrm{ch},t} + B_{\mathrm{dis},t} \le 1 \tag{27}$$

For two consecutive hours t and $t+1$, the available energy in kWh of the battery must follow some continuity, in that, the available energy at time $t+1$ $E_{b,t+1}$ approximately equals the available energy at time t $E_{b,t}$ plus (or minus) the charging (or discharging) power:

$$E_{b,t+1} = \left(1 - \sigma_b\right) E_{b,t} + \Delta t \left(\varepsilon_b P_{\mathrm{ch},t} - \frac{P_{\mathrm{dis},t}}{\varepsilon_b}\right) \tag{28}$$

where σ_b is the battery self-discharging rate; ε_b is the battery charging/discharging efficiency; and Δt is the unit time interval.

The available energy of the battery cannot exceed at any time its rated capacity or fall below zero, i.e.,

$$0 \le E_{b,t} \le S_b \tag{29}$$

Besides S_b, χ, and $P_{\mathrm{ch},t}$, which have appeared in the objective function, other variables that need to be optimized include $P_{\mathrm{grid},t}$, $P_{\mathrm{dis},t}$, $P_{\mathrm{curt},t}$, $E_{b,t}$, $B_{\mathrm{ch},t}$, and $B_{\mathrm{dis},t}$. As $B_{\mathrm{ch},t}$ and $B_{\mathrm{dis},t}$ are binary integers, the minimization problem in (20) is a mixed-integer linear programming (MILP), for which standard solvers exist. To perform the optimization, non-variable parameter values should be first sought, typically from the literature. In this paper, the values are selected as $r=8\%$ [35], $\zeta_s=1\%$, $\zeta_b=0.02\%$ [9], $l_s=30$ years, $l_b=15$ years [36], $\sigma_b=0.01\%$ [35], $\varepsilon_b=95\%$ [35], $c_s=857$ \$/kW, and $c_b=137$ \$/kWh [33], [34]. Lastly, (28) is iterative, thus a starting value $E_{b,1}=0.8S_b$ is assumed, i.e., the initial available energy is 0.8 times the rated capacity [12]. The mathematical description of firm forecasting is then complete. It is worth noting that if $P_{\mathrm{fcst},t}$ in (23) is replaced by load, with the rest being kept unchanged, the above procedure becomes the optimization for firm generation as appeared in [12].

III. CASE STUDY

A. Data

This paper considers the Solar Power Data for Integration Studies (SPDIS), which is the data product of a three-phase project namely the Western Wind and Solar Integration Study, led by the National Renewable Energy Laboratory in USA. The SPDIS dataset contains two kinds of files, PV power generation (i.e., simulated "actuals") and their corresponding forecasts. The PV power is simulated via the sub-hour algorithm in [37] with 5 min resolution. Meanwhile, the day-ahead forecasts, which are in hourly resolution, are produced by a commercial forecast provider namely 3Tier [38], who generates the forecasts based on NWP. Both observation and forecast span a full year (2006), for approximately 6000 locations in the USA. In this paper, a subset of SPDIS is selected, with 405 PV plants in the state of California, USA, as shown in Fig. 1(a).

As the first step, the 5 min actual PV power data are aggregated to an hourly resolution to match the resolution of the 3Tier forecast. Next, the PV systems are framed into a two-level hierarchy based on the 500 kV substations. The PV-to-substation assignment is done with the nearest neighbor method, in which each system is allocated as a bottom-level node for the substation nearest to it. Figure 3 visualizes the assignment, with substations being $\mathcal{L}_1$ and PV plants being $\mathcal{L}_2$. Table I shows the metadata of the 500 kV substations, alongside the number and installed capacity of PV systems assigned to each substation.

The 3Tier forecasts are available for each PV plant. These are bottom-level (or $\mathcal{L}_2$) base forecasts. To generate the upper-level forecasts, a time series method is used. Knowing that PV power exhibits diurnal transient, the autoregressive integrated moving average (ARIMA) model with Fourier terms (AFT) is thought adequate. AFT first fits a Fourier series to the PV power data, and models the remainder with ARIMA. AFT is applied for each top-level (or $\mathcal{L}_0$) and middle-level (or $\mathcal{L}_1$) series, separately. For each series, forecasts are produced in a rolling manner: data from January 1-7 are used to train the first AFT model, and forecasts for January 8 are produced; then data from January 2-8 are used to train the second AFT model, and forecasts for January 9 are produced. This continues until the forecasts for December 31 are produced.

With the base forecasts for all levels being ready, two reconciliation methods are used to produce reconciled forecasts, namely MinT (mentioned in Section II-B) and BU reconciliation, which simply sums up the $\mathcal{L}_2$ forecasts to form aggregate consistent $\mathcal{L}_0$ and $\mathcal{L}_1$ forecasts. Whereas BU reconciliation does not require training, MinT reconciliation does. The one-year dataset is split into two halves chronologically. MinT is first trained with data from the first half of year, and out-of-sample reconciled forecasts are produced for the second half of year. Then, MinT is trained with data from the second half of year, and out-of-sample reconciled forecasts are produced for the first half of year. As such, one full year of MinT-reconciled forecasts is obtained.

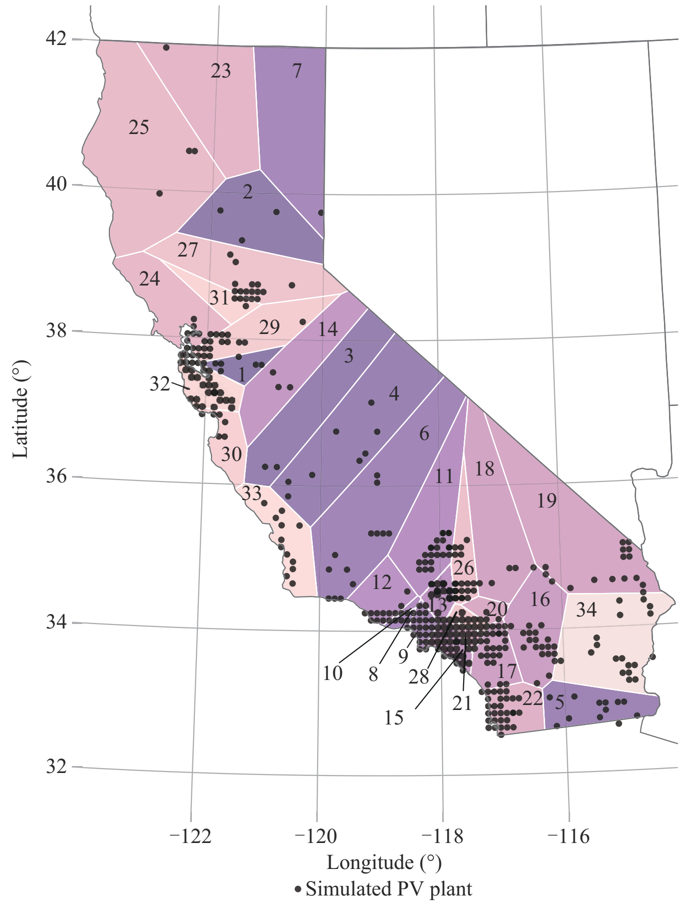

Fig. 3. Assignment of 405 simulated PV plants to their nearest substations forming a two-level hierarchy.

B. Firm Forecasting at Substation Level

In this subsection, firm forecasting is conducted at the substation level (i.e., $\mathcal{L}_1$). Several important quantities pertaining to firm forecasting are first explained. The firm forecast premium, which is an overall indicator of the cost-effectiveness of firming up variable solar power generation, can be interpreted as the cost multiplier for meeting the forecast amount of PV power with absolute certainty. Firm forecast premium may be visualized as a function of the overbuilding ratio, which is the capacity multiplier to the original installed PV capacity, e.g., an overbuilding ratio of 2 means expanding whatever original installed capacity by two times. Battery storage required to firm up uncertain forecasts can be gauged in its usual unit, i.e., MWh or kWh. Last but not least, it is of interest to quantify the additional cost in \$/kW, which indicates how much additional monetary investment is necessary to firm up a unit PV capacity. This quantity is called \$/kW premium. All the above-mentioned quantities have a negative orientation, i.e., the lower their values are, the more amenable the strategy is.

To give perspective on interpreting the firm forecasting results, Fig. 4 shows the firm forecast premium against the overbuilding ratio for substation 8. Forecasts from both the BU and MinT reconciliations are considered and firmed up by strategies of different combinations of battery and overbuilding.

TABLE I
METADATA OF 500 kV SUBSTATIONS, ALONGSIDE NUMBER AND INSTALLED CAPACITY OF PV SYSTEMS

No.	Longitude (°)	Latitude (°)	Name	Number of PV systems	Capacity of PV systems (MW)
1	–121.56	37.71	Tesla	7	171
2	–121.64	39.56	Table Mt.	3	136
3	–120.70	36.72	Oxford	2	225
4	–120.13	36.14	Gates	8	759
5	–115.72	32.72	Imperial Valley	12	965
6	–119.45	35.40	Midway	13	813
7	–120.50	40.96	Madeline	1	7
8	–118.48	34.28	Rinaldi	6	630
9	–118.39	34.24	Sta. M (Valley)	18	1866
10	–118.49	34.31	Sylmar	1	121
11	–118.30	34.69	Antelope	24	1429
12	–118.58	34.44	Pardee	12	650
13	–118.12	34.49	Vincent	14	966
14	–121.02	37.05	Los Banos	3	68
15	–117.79	33.83	Serrano	30	2564
16	–116.58	33.94	Devers	22	1290
17	–117.16	33.74	Valley	24	1005
18	–117.32	34.56	Victorville	5	652
19	–115.52	35.25	Cima	14	1928
20	–117.37	34.37	Lugo	3	306
21	–117.56	34.01	Mira Loma	10	482
22	–116.98	32.68	Miguel	30	451
23	–121.94	40.81	Round Mt.	1	11
24	–121.92	38.40	VD&G Yard	12	224
25	–122.38	40.38	Olinda	3	112
26	–117.44	34.55	Adelanto	20	1126
27	–121.72	39.02	O'Banion	14	332
28	–117.53	34.09	Rancho Vista	10	465
29	–121.58	37.80	Tracy	16	378
30	–121.78	36.81	Duke Energy	6	36
31	–121.92	38.41	Calpeak Power	4	64
32	–121.75	37.23	Metcalf 2	27	531
33	–120.85	35.22	Diablo Canyon	12	169
34	–115.56	33.67	Capacitor	18	1571

The figure displays how battery (orange line) and PV (blue line) contribute to the overall firm forecast premium (green line), i. e., the green line is the sum of the orange and blue lines. Several points are marked in the figure, with the first number in each pair of parentheses being the overbuilding ratio and the second being the firm forecast premium. Point A corresponds to the situation with unconstrained PV, which in itself, though inexpensive, is not firm. To firm up the unconstrained PV with a storage-only solution (i. e., no overbuilding), an exceedingly high capacity of battery is needed, which in turn drives up the premium substantially (26.75 for BU or 13.82 for MinT). This situation is marked as point B. At point C, the firm forecasting strategy is optimal, which corresponds to the combination of battery and overbuilding that gives the lowest premium (2.46 for BU or 2.04 for MinT).

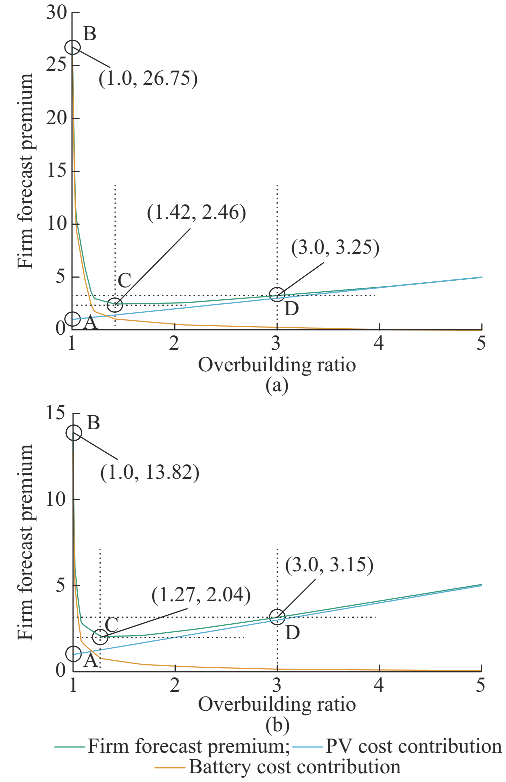

Fig. 4. Firm forecast premium against overbuilding ratio for substation 8. (a) BU. (b) MinT.

Then, as the overbuilding ratio continues to increase, the firm forecast premium is dominated by PV cost, and thus starts to rise linearly. Point D shows the premium at an overbuilding ratio of 3 (3.25 for BU or 3.15 for MinT), which is higher than the optimal premium.

Figure 4 reveals that MinT, as a more advanced reconciliation technique that produces better forecasts than BU, can lead to quantifiable benefits in terms of firm forecast premium, insofar as the scenario at substation 8 is concerned. For other substations, the additional cost to firm up forecasts (i.e., $/kW premium) is plotted against the reconciled forecast root-mean-square error (RMSE), as shown in Fig. 5. As can be seen, the linear fits with standard error bounds (blue areas) in both cases show upward trends. The $/kW premium generally increases as forecast RMSE gets large. Obviously, although one may reasonably assume that the statement "better forecast means lower premium" is generally true, the following results partially dismiss that.

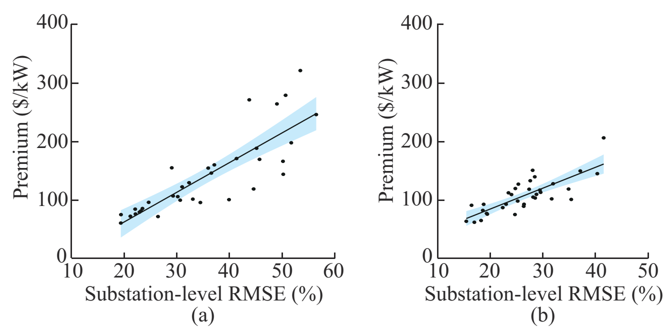

Fig. 5. Substation-level RMSE versus $/kW premium using two reconciliation methods. (a) BU. (b) MinT.

Table II tabulates the firm forecasting results at substation level using BU and MinT reconciliation methods. The first two columns show the substation index and total installed capacity. The last two columns show the additional cost required per kW PV with the current market price to turn unconstrained PV into firm PV. It can be observed that the firm premium of BU is often found lower than that of MinT. More generally, there does not seem to be any noticeable pattern that can be used to conclude how a lower overbuilding ratio and a lower battery capacity can be achieved simultaneously. Based solely on the premium, the MinT, which provides motivation for improving accuracy, appears to have led to a lower overall cost as shown in the last two rows of Table II.

TABLE II
FIRM FORECASTING RESULTS AT SUBSTATION LEVEL USING BU AND MINT RECONCILIATION METHODS

Index	Capacity (MW)	RMSE (%)		Firm premium π		Overbuilding ratio		Battery capacity (MWh)		Premium ($/kW)	
		BU	MinT	BU	MinT	BU	MinT	BU	MinT	BU	MinT
1	171	45.7	28.5	2.79	2.18	2.10	1.61	802	547	170	104
2	136	49.0	31.9	3.54	2.48	3.03	1.86	753	453	264	129
3	225	39.9	28.8	2.30	2.31	1.34	1.55	978	867	101	110
4	759	26.5	22.4	1.91	2.05	1.43	1.51	1651	2077	73	88
5	965	19.4	15.4	1.66	1.76	1.36	1.29	1781	2358	62	65
6	813	24.7	23.0	2.08	2.11	1.51	1.36	2676	3154	97	94
7	7	45.2	34.9	2.91	2.35	1.65	1.15	57	45	189	120
8	630	32.4	26.3	2.46	2.04	1.42	1.27	3667	2550	130	90
9	1866	30.7	24.7	2.09	1.88	1.67	1.41	4935	4621	100	76
10	121	36.0	29.6	2.72	2.31	1.47	1.22	855	698	155	114
11	1429	23.2	19.4	1.86	1.89	1.33	1.13	4636	5653	82	77
12	650	29.1	24.0	2.69	2.27	1.46	1.26	4670	3477	156	110
13	966	23.5	19.3	1.92	1.90	1.39	1.30	3120	3076	86	78
14	68	43.8	28.0	4.10	2.79	1.31	1.10	1031	595	271	151
15	2564	37.1	28.4	2.68	2.61	2.67	2.22	2995	5817	161	140
16	1290	21.2	17.0	1.76	1.74	1.41	1.28	2963	3049	73	63
17	1005	29.3	23.4	2.21	2.34	1.24	1.20	5337	5886	108	113
18	652	22.1	18.7	1.91	2.09	1.44	1.33	1893	2625	85	93
19	1928	22.2	18.2	1.83	1.77	1.40	1.30	4968	4732	77	66
20	306	31.0	24.8	2.36	2.42	1.32	1.65	1781	1229	123	120
21	482	33.1	26.4	2.09	2.10	1.47	1.31	1820	1963	102	94
22	451	36.6	27.6	2.60	2.56	2.14	1.81	1376	1809	147	134
23	11	56.5	41.5	3.73	3.45	2.38	1.68	86	99	246	207
24	224	50.2	37.1	2.51	2.66	1.46	1.93	1714	975	167	150
25	112	51.8	40.3	2.99	2.68	1.78	1.58	899	654	198	146
26	1126	23.0	18.6	1.84	1.96	1.21	1.20	4169	4494	80	83
27	332	53.5	27.4	3.89	2.36	2.82	1.69	3394	1220	321	119
28	465	30.2	25.2	2.15	2.17	1.31	1.12	2274	2498	107	99
29	378	41.4	28.1	2.73	2.20	1.35	1.72	3262	1030	171	106
30	36	50.2	35.4	2.51	2.16	2.21	1.63	91	105	145	102
31	64	50.7	29.4	3.60	2.34	2.94	1.97	450	137	279	118
32	531	44.6	31.6	2.29	2.16	1.61	1.65	2176	1538	120	103
33	169	34.5	25.3	2.11	2.50	1.50	1.18	557	1165	97	128
34	1571	19.4	16.4	1.85	2.09	1.47	1.38	3468	5797	76	92
Overall	22503	28.9	22.7	2.29	2.12	1.62	1.45	77284	76993	109	95

Nonetheless, it is also true that more accurate forecasts do not necessarily lead to more economic firm forecasting. Reference [39] attributes the reason to the fact that some methods can produce balanced under- and over-forecasts, which is in favor of the storage management, in that it does not demand large storage size to cater for prolonged over- or under-forecast situations.

C. Firm Forecasting at Individual Plant Level

Different from the previous subsection, this subsection investigates firm forecasting that is conducted at the individual plant level (i.e., $\mathcal{L}_2$). This option of firm forecasting is reasonable, because the power grid may not want to be the sole bearer of the cost for attaining firm forecasting, but rather prefer to distribute the cost to individual plant owners, who are in any case motivated to submit good forecasts, owing to the penalty schemes. In fact, many power systems have already seen increasing interest in pairing energy storage with distributed power systems [40].

Both the BU- and MinT-reconciled forecasts at $\mathcal{L}_2$ are used to study firm forecasting at the plant level. It should be noted that the BU forecasts at $\mathcal{L}_2$ are no different from the raw 3Tier forecasts. Figure 6 plots the differences in $/kW premium of firm forecasting based on 3Tier and MinT-reconciled forecasts. The differences are calculated using the $/kW premium of 3Tier forecasts minus that of MinT-reconciled forecasts, so a positive difference indicates that firm forecasting with 3Tier forecasts is more costly than that with MinT-reconciled forecasts, and a negative difference indicates that firm forecasting with MinT-reconciled forecasts is more costly than that with 3Tier forecasts. It can be observed that most plants see a positive difference, which means better forecasts are rewarded with a smaller $/kW premium. There are some sites at which opposite results are obtained, where 3Tier forecasts are less costly to firm up than MinT-reconciled forecasts. However, as evidenced by the faint shades of blue shown in Fig. 6, the negative differences are usually minor, confirming the overall benefits of using forecasts of higher quality. Quantitatively, it is noted that the maximum positive difference reaches 244.74 $/kW, whereas the minimum negative difference is −58.91 $/kW.

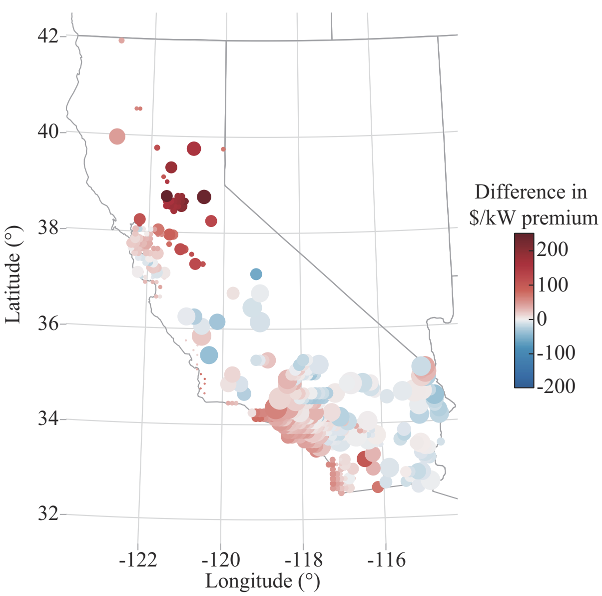

Fig. 6. Differences in $/kW premium of firm forecasting based on 3Tier and MinT-reconciled forecasts at individual plant level.

To compare the results of firm forecasting at the individual plant level with that at the substation level, the firm premium, overbuilding ratio, battery capacity, and $/kW premium at the individual plants are aggregated to their respective substations, of which the results are listed in Table III. It is found that irrespective of the metric or reconciliation method, firm forecasting at the individual plant level is less cost-effective than firm forecasting at the substation level. For instance, at substation 1, substation-level firm forecasting based on MinT has the premium of 104 $/kW, whereas the aggregated plant-level firm forecasting based on MinT has the premium of 135 $/kW. These results can be explained from the perspective of geographical smoothing. When multiple plants are firmed up jointly, individual plant variability is smoothed out, resulting in a milder transient that is easier to forecast and thus easier to firm up. Figure 7 shows the comparison of $/kW premium in the form of bar charts, and the advantage of firm forecasting at the substation level is immediately obvious. From the magnitudes of the bars, it can be confirmed again that MinT-reconciled forecasts are easier to firm up than BU-reconciled forecasts. The general rule revealed in Fig. 7 can also be observed when comparing the values of the last two rows of Tables II and III.

TABLE III
FIRM FORECASTING RESULTS AT INDIVIDUAL PLANT LEVEL USING BU AND MINT RECONCILIATION

Index	Capacity (MW)	Firm premium π		Overbuilding ratio		Battery capacity (MWh)		$/kW premium	
		BU	MinT	BU	MinT	BU	MinT	BU	MinT
1	171	3.13	2.53	1.83	1.59	1362	885	201	135
2	136	4.57	3.36	2.78	2.21	1783	841	366	205
3	225	2.34	2.41	1.57	1.65	761	867	105	119
4	759	2.71	2.74	1.66	1.75	3823	3809	139	146
5	965	1.99	2.07	1.44	1.28	3135	3922	91	91
6	813	2.62	2.69	1.62	1.67	4491	4290	143	143
7	7	2.91	2.35	1.65	1.15	57	45	189	120
8	630	2.50	2.11	1.56	1.39	3318	2373	134	96
9	1866	2.53	2.29	1.89	1.64	7229	6412	139	111
10	121	2.72	2.31	1.47	1.22	855	698	155	114
11	1429	2.10	2.13	1.38	1.26	6099	6442	104	98
12	650	2.89	2.48	1.72	1.42	4481	3650	173	129
13	966	2.14	2.17	1.40	1.31	4166	4315	106	101
14	68	4.10	2.80	1.31	1.10	1030	595	272	152
15	2564	3.00	2.84	2.49	2.18	9760	9479	189	161
16	1290	2.23	2.26	1.62	1.47	4885	5277	116	108
17	1005	2.37	2.46	1.38	1.29	5413	6053	122	124
18	652	1.98	2.12	1.30	1.26	2551	2912	91	96
19	1928	2.05	2.11	1.30	1.31	8154	7939	96	95
20	306	2.47	2.64	1.33	1.48	1940	1833	133	139
21	482	2.30	2.32	1.50	1.32	2281	2505	121	113
22	451	2.89	2.74	2.04	1.82	2321	2186	172	149
23	11	3.73	3.45	2.38	1.68	86	99	246	207
24	224	2.94	2.87	1.90	1.81	1794	1374	210	170
25	112	3.04	2.79	1.86	1.64	882	691	203	156
26	1126	2.05	2.25	1.40	1.30	4315	5588	99	108
27	332	4.11	2.58	3.01	1.71	3490	1586	344	139
28	465	2.31	2.25	1.47	1.29	2267	2301	121	106
29	378	3.24	2.78	1.71	1.63	3644	2367	219	157
30	36	2.58	2.43	2.14	1.54	117	173	151	126
31	64	3.74	2.39	3.04	1.80	470	214	293	122
32	531	2.55	2.52	1.61	1.58	2883	2733	142	134
33	169	2.43	2.65	1.57	1.41	772	1098	123	141
34	1571	1.95	2.14	1.39	1.29	4943	6769	85	96
Overall	22503	2.59	2.41	1.67	1.52	105559	102319	135	119

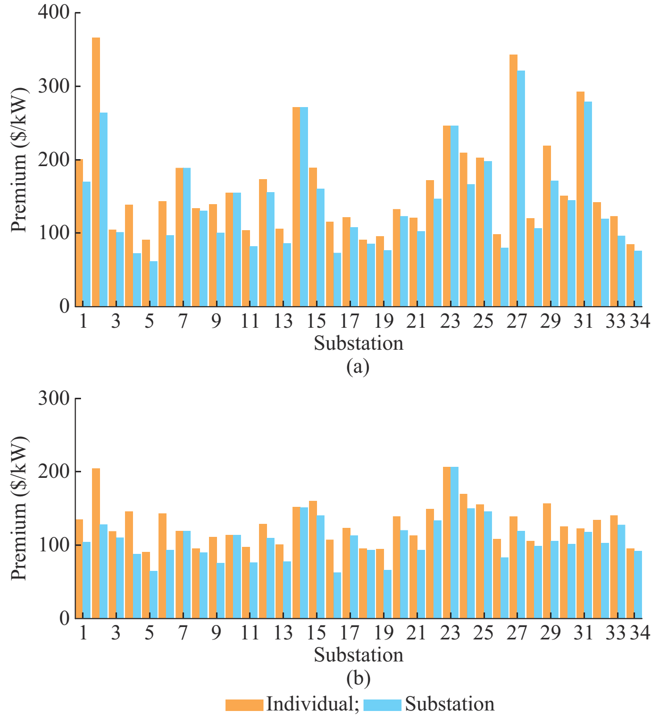

Fig. 7. Comparison of $/kW premium of firm forecasting at individual plant level and at substation level. (a) BU. (b) MinT.

IV. Conclusion

The main contribution of this paper is to integrate the concepts of hierarchical forecasting and firm forecasting into the existing solar power forecasting framework that is widely supported by grid integration policies. Existing solar forecasting for grid integration purposes consists of three steps: ① national weather centers issue NWP forecasts to PV system owners and solar forecast providers, ② the weather forecast users post-process the received forecasts based on local information, and ③ the post-processed weather forecasts are converted to PV power output forecasts and submitted to grid operators. These three steps depict a two-way information flow among various entities relevant to grid integration. Moving beyond the status quo, grid operators should reconcile the received forecasts with their own nodal- or substation-level forecasts, to enhance the quality of forecasts as well as to obtain a set of aggregate consistent forecasts that is conducive to decision-making as a whole. Since reconciled forecasts still contain sizable errors that limit the confidence in the subsequent power system operations, firming up the forecasts through battery storage and PV overbuilding is an attractive course of action, as such the PV plants can guarantee to deliver the same amount of energy as they forecast to deliver, making them effectively dispatchable.

Through a case study with 405 PV plants in California, USA, several findings emerge. Most important among those is that performing firm forecasting at the individual plant level is less economic than that at the nodal or substation level. This conclusion agrees with the implications of the widely known effect of geographical smoothing, which is another major firm forecast enabler besides storage, demand response, and overbuilding. Firm forecasting at the substation level suggests the need for energy storage sharing, which is an increasingly popular research topic [41], and this paper gives a concrete quantification of how much storage is needed in line with the current forecasting framework. Another important finding is that, comparing the BU- and MinT-reconciled forecasts, the latter generally requires a lower overbuilding ratio to achieve firm forecasting, which contributes to the overall lower $/kW premium. More specifically, calculating the weighted average $/kW premium based on the numbers in Table I, the overall $/kW premium of the 405 PV plants in California is 109 $/kW if firm forecasting proceeds from BU-reconciled forecasts, whereas the number lowers to 95 $/kW if firm forecasting proceeds from MinT-reconciled forecasts. Insofar as the current comparison is concerned, there is sufficient motivation to work toward better reconciled forecasts.

One limitation of the proposed framework is that it does not consider uncertainty. There are several sources of uncertainty that could affect the eventual quantification of the firm forecast premium. For instance, the solution of the current mix-integer linear programming (20)-(29) depends on the particular set of forecast and production time series entering the optimization. However, the PV generation and forecast errors can change substantially over different years, which can render the firm forecast premium higher or lower. Another source of uncertainty originates from continuous technology development, which may gradually lower the cost of PV and batteries over time. Therefore, it is important to consider at least three directions for future research. First, the effect of inter-annual variability in future solar irradiance and thus future PV power should be quantified. This can be done by considering climate models, which issue irradiance projections over several future decades. Second, the uncertainty of forecast errors may be further analyzed by trying different forecasting methods and over different years. Third, optimization methods that consider uncertainties, such as robust optimization or stochastic programming, should be taken into consideration. However, all three future directions for research in firm forecasting require careful design of experiments, e.g., the choice of spatial downscaling used for climate models or the distributional assumptions used in stochastic programming. It is believed that firm forecasting has growing interests and presents a promising avenue toward dispatchable solar power in modern power systems.

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