Corrective dispatch of uncertain energy resources using chance-constrained receding horizon control

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Abstract—High penetrations of intermittent renewable energy resources in the power system require large balancing reserves for reliable operations. Aggregated and coordinated loads can provide these fast reserves, but represent energy-constrained and uncertain reserves (in their energy state and capacity). To optimally dispatch uncertain, energy-constrained reserves, model predictive control offers a viable tool to develop an appropriate trade-off between closed-loop performance and robustness of the dispatch. Therefore, this paper investigates the uncertainty associated with energy-constrained aggregations of flexible distributed energy resources (DERs). The uncertainty studied herein is associated with estimating the capacity of and the estimated state of charge from an aggregation of DERs. To that effect, a risk-based chance constrained MPC (RB-CC-MPC) is developed that co-optimizes the operational risk of prematurely saturating the (virtual) energy storage against deviating generators from their scheduled set-point. On a fast minutely timescale, the RB-CC-MPC coordinates energy-constrained virtual resources to minimize unscheduled participation of and overcome ramp-rate limited generators for balancing variability from renewable generation, while taking into account grid conditions. To illustrate the effectiveness of the proposed method, simulation-based analysis is carried out on an augmented IEEE RTS-96 network with uncertain energy resources.

Index Terms—model predictive control, chance constrained, robust optimization, energy constrained resources, multi-period optimal power flow

I. INTRODUCTION

Conventional generators, such as fast-ramping gas generators, have provided reliable balancing reserves to meet the variability of traditional demand. However, with the increasing penetration of wind and solar PV resources in power systems, more fast reserves are required, which leads to more conventional generators being operated at reduced power or even idling and is economically inefficient and increases harmful emissions. Rather than matching the net-load variability (i.e., demand minus renewable generation) with more conventional reserves, controllable and flexible loads can be coordinated (i.e., aggregated) to ensure reliable operation [1]. While the core concepts of demand response (DR) have been proposed decades ago [2], [3], the DR technology available today is still in its early stages, but maturing rapidly [4], [5].

Virtual power plants (VPPs) have been proposed as a concept for aggregating and coordinating distributed energy resources to provide synthetic (i.e., demand side) reserves for the grid operators in support of a responsive grid [7]. Due to energy balance in power systems, control actions that increase (decrease) in conventional generators power have the same effect as decreases (increases) in the power consumed by VPPs. Thousands of DERs such as thermostatically controllable loads (TCLs) and electrical vehicles can be effectively aggregated to form a VPP. However, a DER has its own baseline consumption that is a function of many exogenous and uncertain parameters (e.g., hot water usage, arrival or departure time of EVs, etc.). In addition, they are not each under the direct control of the operator. Furthermore, unlike a grid-scale battery, a VPP’s energy state, energy capacity, and power limits (i.e., its flexibility) are inherently time-varying and uncertain. Thus, to benefit the most from the availability of uncertain, energy-constrained reserves, careful design of control techniques is required and model predictive control (MPC) represents a useful strategy to design VPP dispatch algorithms.

The MPC strategies have been widely used in power systems for optimized coordination of grid resources, including demand and energy storage applications, e.g., please see [8], [11]. The main purpose of those strategies centers around contingency management, voltage stability, congestion control of transmission line and energy management. For a general overview of MPC, please see [12]. MPC operates the system over a receding horizon by considering net-load forecasts and power and energy states of the flexible resources. This makes MPC a particularly useful method within which, one can study trade-off between dispatching ramp-rate limited conventional generators and energy-constrained, uncertain VPP resources.

This work extends prior results by the authors on the multi-period optimal dispatch of uncertain flexible energy resources [11]. Contributions in this manuscript include the following:

- The MPC scheme in this work was inspired by the author’s prior work in which deterministic bulk battery storage was optimally dispatched to reject large grid disturbances [9], [10]. Their models included a transmission system with dynamic line temperature ratings to provide a feedback mechanism. However, the role of uncertain grid resources was not considered in those prior works.
- Authors in [13], [14] developed a reserve scheduling framework that manages uncertain renewable power production and demand-side reserves, taking into account uncertainty in the energy state of controllable load over multiple periods. Their work focuses on solving a reserve market clearing problem every 15 minutes. However, we focus on dispatching balancing reserves on a faster timescale and consider additional uncertainties.
- As far as the authors are aware, prior work on stochastic optimal power flow (OPF) methods, focuses mainly on the uncertainty of (algebraic) power injections (e.g., wind, demand), which temporally decouples the OPF problem and side-steps the computational challenges of multi-period optimization under uncertainty, e.g., [15], [16]. Unlike those works, this paper presents a stochastic, predictive, and dynamic OPF framework with uncertain estimates for state of charge and energy capacity. Related work in [17] investigates optimal sizing and receding-horizon dispatch of bulk batteries under uncertainty in wind generation, which gives rise to chance-constrained MPC formulation that is valuable for planning studies. Our work focuses on corrective operations.
The resulting schedule includes optimal generator set-points and the reference trajectory is computed as a multi-period quadratic problem (QP) that seeks to minimize the operational cost while allowing computation of an economically optimal, secure schedule for generators and flexible resources for a number of hours [18]. Thus, linear interpolation is employed between reference trajectory value computed on outer loop. The corrective MPC scheme can be summarized by the following process:

1) At time $k$, with estimates of initial state of the charge (SOC), line temperatures, generators’ operating point, updated net-load forecasts and updated generator trajectory from SC-OPF, the MPC solves a finite-horizon open-loop optimal control problem, over interval $[k,k+M]$. This produces a schedule of control actions that describe charging (discharging) rates for VPPs and re-dispatch signals for generators.
2) Apply only the control actions corresponding to time $k$.
3) Measure/estimate the system’s dynamic states based on the realized demand and renewable generation at time $k+1$.
4) Go to 1.

The open-loop MPC optimization is defined for a power system network $G = (\mathcal{V}, \mathcal{E})$ with bus $i \in \mathcal{V}$ and lines $ij \in \mathcal{E}$ such that minimizing deviation of generator outputs from the scheduled set-points and preventing line overloads as follows

$$\min \sum_{l=k}^{k+M} \left( \sum_{\forall i \in \mathcal{N}_g} c_{G,i} \left( P_{G,i}^l - P_{G,i}^{ref} \right)^2 \right) + \sum_{\forall ij \in \mathcal{E}} c_{P,ij} \Delta T_{ij}^2$$

s.t. [Equation va]
where the four groups of constraints in the MPC formulation are challenging. To ensure a tractable approach at the timescale of interest, a suitable linear approximation of the AC power flow equation (i.e., "Lossy DC") has been adopted. Since the MPC executes on a fast timescale and the linearized model is updated under a feedback mechanism by estimating line losses and temperatures, the model is accurate for control [9][10].

The power carrying capacity of a transmission line is determined based on the (static) thermal rating of the conductors, which is suitable for hourly energy management schemes. However, for short term operations, the line flows may exceed power limits for short durations without violating the (dynamic) temperature limits of the lines. Since MPC re-initializes every minute, line overloads are regulated by the conductor temperatures, and the controller seeks to alleviate sustained temperature overload.

In general, a DC formulation is based on lossless network models. However, the heat gain is a function of ohmic losses (i.e., $RT^2$). To regulate line temperature limits, it is necessary to include line losses in the power flow model. We approximate line losses in proportion with the square of the DC-based power flow as shown in (1c).

Thus, line losses are non-convex in $\theta_{ij}$, so a convex relaxation is employed (i.e., $P^\text{loss} = R_{ij}^2\theta_{ij}^2$) that is provably binding at optimality for lines that are overloaded since $\Delta T_{ij}$ is in the objective function. This achieves the desired measure of control over the line flows. Please see [10] for proof.

IEEE Standard 738 [21] defines the current-temperature relationship of bare overhead conductors and has been employed herein to calculate the conductor temperature. To allow for a tractable implementation of MPC scheme, temperature dynamics of transmission lines are linearized around the equilibrium point $T^* = T^\text{lim}$, where $T^\text{lim}$ is computed from steady-state conditions with line current at ampacity (i.e., set $P^\text{loss} = R_{ij}(I^\text{lim})^2$), where $R_{ij}$ is the per-unit resistance of line $ij$.

The MPC scheme computes control actions that drive line temperatures below limits, and as long as they are below limits, there is no benefit in further reducing line temperatures. A measure of temperature that aligns with such an objective is given by (11). This constraint is equivalent to $0 \leq \Delta T_{ij}$ and $\Delta T_{ij} \leq \Delta T_{ij}$. 

### A. Power balance in (1b)

Based on Kirchoff’s laws, the net power flow into any node must equal the net power flow out. Generators may inject power, $P_G$, and loads may consume power $P_L$ at each node $i$. If VPPs are available at a node, then positive (negative), $P_B$, corresponds to additional consumption (generation).

### B. Conventional generators in (1c) to (1d):

Each conventional generator is described by its production state, which must be within generator limits, as shown in (1c). Furthermore, due to the thermal nature of the generators, the ramp rate of generators are limited to their ramp up (down) limit, $R_{ij}$, as shown in (1d). The responsive VPPs overcome limitations of generator ramping rates.

### C. Transmission lines in (1e) to (1p):

In general, the AC power flow between bus $i$ and $j$, $p_{ij}$, is the solution to a set of nonlinear, algebraic equations. The nonlinearity renders the multi-period AC-OPF problem computationally challenging. To ensure a tractable approach at the timescale of
that underpin them. That is, in general, coordination schemes do not offer instant control over all DERs in a fleet, but are subject to separate internal control, actuation, and communication loops. These cyberphysical control considerations manifest themselves as ramp-rate limits on the charging ($R_{ch}$) and discharging ($R_{dis}$) of VPPs as shown in (1n) and (1o). Note that the results in this manuscript are agnostic to the specifics of the coordination scheme.

At high levels of renewable penetration, a VPP’s responsiveness (compared with a conventional generator) makes it a valuable resource to overcome imbalances in demand and supply. However, unlike a conventional generator, the VPP’s energy-constrained characteristics necessitate careful management of its state of charge. Furthermore, unlike grid-tied batteries, the amount of flexibility available to the system operator is time-varying and uncertain. That is, the flexibility available to the system operator from a VPP can be translated into an upper limit on the VPP’s energy value. This upper bound is a function of different stochastic quantities, such as human behavior and weather. To capture these considerations, VPPs herein are formulated probabilistically and are modeled with chance constraints.

### IV. Uncertainty Management

The flexibility provided by a VPP’s aggregated DERs can be viewed by the system operator as a grid-scale battery. Since DERs are subject to micro-level background effects (such as hot water usage, EV driving patterns, and battery/solar PV effects) but VPPs represent a macro-level object, the effect of the time-varying and stochastic background processes are realized in the form of uncertain energy bounds and states. For example, the upper energy limit of the VPP is uncertain and must be estimated and predicted from a separate model. Considering the central limit theorem, the flexibility offered by each device is uncertain and represents an independent random variable (i.e. background usage of each device is independent). Therefore, a VPP’s energy capacity can be approximated as a normally distributed random variable centered on the true mean (i.e. $\mathbb{E}[P_{B,i}] \sim \mathcal{N}(\mathbb{E}[P_{B,i}], \sigma^2)$). Moreover, in contrast with the grid-scale batteries, the actual SOC of the VPPs can not be measured directly and a dynamic state estimation method (e.g. an Extended Kalman Filter) should be employed to estimate the SOC of a VPP at each time step. State estimation of a VPP’s SOC is subject to uncertainty inherent in any state estimation method. In addition, due to the nature of Kalman filters, the noise process can be assumed normally distributed and centered on the true mean (i.e. $S_{k}^{net} \sim \mathcal{N}(S_{k}^{net}, \sigma^2)$). An illustration of the uncertain estimation of a VPP’s energy capacity and SOC is illustrated in Fig. 2.

**Definition IV.1 Dynamic capacity saturation:** Uncertain VPP control actions such as charging and discharging commands can be optimized based on a mean (or average) energy capacity estimate alone (i.e., first moments). In that case, using just the expected energy capacity value (and ignoring higher moments, such as variance) can result in simple deterministic optimization problem. However, the underlying, uncertain VPP energy capacity may realize itself unexpectedly and saturate in the energy state, which zeros out the charging rate of the optimized control (power) action. We call this saturation phenomenon dynamic capacity saturation (DCS) [11]. This can yield large unexpected power imbalances in a power system. To regulate these unexpected DCS-induced power imbalances, grid operators must rely on (expensive) generation to supply the difference.

#### A. The Chance Constrained Formulation

Chance constrained optimization is employed to reduce the effect of DCS and to solve an optimization problem with various uncertainties under which the constraints must be satisfied only with a some predefined desirable probability level $1-\epsilon$, where $\epsilon \in (0, 1)$ is the violation level. Reducing risk increases system reliability, but also operational cost, which represents a clear trade-off. Within the context of pay-for-performance ancillary services, the operational costs are defined herein by the generators reference-tracking errors of the inner loop [25].

Chance constrained optimization problems can be solved with a probabilistically robust scheme, inspired by the so-called scenario approach. In the scenario approach, the chance constraint is substituted with a finite number of deterministic constraints corresponding to different realizations of the underlying uncertainty space [26]. By employing an adequate number of scenarios from this set (i.e. $N >> 1$), the approach is able to provide a-priori guarantees of satisfying the chance constraint. The scenario-based approach is useful in offline planning studies as it makes no assumption on the underlying distribution of the uncertainty. However, the number of scenarios required is a function of $\epsilon$ and the number of uncertain variables and can grow very large. In addition, and more crucially, the scenario-based approach is most useful when the uncertainty is complex and captured via large data sets. In addition, if the underlying problem is convex, there exists techniques to reduce the number of scenarios and mitigate computation costs by reformulating the problem into a robust optimization problem [27].

Indeed, if an accurate analytical model of the uncertainty distribution is known, the method analytical reformulation can be employed to transform the chance constraint into a robust, deterministic constraint [28-29]. In contrast to the scenario approach, the analytical reformulation does not require sampling complex distributions or large data-set. This means that only a single reformulation for each chance constraint is needed, which makes implementation tractable at the timescale of interest [30]. Because the estimation of capacity and SOC of the VPPs are assumed to be normally distributed random variables (due to aggregation of many stochastic background processes), the chance constraint can be reformulated analytically.
Next, we introduce the chance constraints related to the uncertain variables of the VPP (i.e., energy capacity and SOC) and briefly describe the analytical reformulation to derive a convex program. The formulation is presented with respect to the upper energy capacity limit of the VPP, but the lower limit can be handled in a similar manner.

1) Analytical reformulation of chance constrained problem regarding the uncertain estimation of VPP SOC: Recall, the evolution of the SOC of a VPP over the prediction horizon, is related to the estimated SOC at time \( k \) (i.e., \( S_k \)) and charging (discharging) control actions as follows

\[
S[l] = S_k + \sum_{m=1}^{l} \Delta S[m]
\]

where \( \Delta S[l] = T_s (\eta_{ch} P_{ch}[l] - \eta^{-1}_{dis} P_{dis}[l]) \). Since the estimated SOC of VPP is assumed to be a normally distributed random variable centered on the true mean, the chance constraint is formulated as follows

\[
P(S^\text{act}[l] \leq S^\text{est}) \geq 1 - \epsilon_1,
\]

with \( S^\text{act}[l] = S^\text{act} + \sum_{m=1}^{l} \Delta S[m] \).

Thus, the probabilistic constraint \( (6) \) can be expressed as

\[
S^\text{est} + \sum_{m=1}^{l} \Delta S[m] \geq \Phi^{-1}(1 - \epsilon_1) \sigma_s
\]

By considering \( (10) \), chance constraint \( (9) \) can be reformulated as

\[
P(S^k_e + \sum_{m=1}^{l} \Delta S[m] \leq \Phi^{-1}(1 - \epsilon_2) \sigma_c) \geq 1 - \epsilon_2
\]

Thus, combining the two sources of uncertainties in \( (8) \) and \( (12) \) yields

\[
\sum_{m=1}^{l} \Delta S[m] \leq \Phi^{-1}(1 - \epsilon_1) \sigma_s - \Phi^{-1}(1 - \epsilon_2) \sigma_c
\]
In applying chance constraints, there is a clear trade-off between high reliability (i.e., very conservative and robust bounds for VPPs) and lower nominal cost (i.e., use as much VPP as possible), which depends on how risk limits are chosen. Risk limits are generally chosen as a predefined parameters (e.g. $\epsilon \in (0.9, 0.99)$) based on the importance of the constraint.

Hence, we propose a novel risk-based approach for time coupled uncertainties that limits the SOC to the robust bound, $\Sigma_{rob}$. The robust bound can be determined by using expert knowledge, employing scenario-based approach or sampling based method, or by using historical data to acquire a distribution of the uncertainty and applying an approach like analytical reformulation based on the identified distributions. In this manuscript, the authors’ previous work [1] is extended to include the robust bound by analytical reformulation of the initial chance constraints.

In the risk-based approach, instead of limiting the SOC of VPPs to a predefined robust bound, the formulation below allows the solution to exceed the robust bound at each point in time. This is possible by introducing as the operating risk, $\mathcal{R}$, which is a new decision variable. Thus, performance and risks can be co-optimized, which leads to the following multi-objective optimization problem:

$$\min_{P_G, P_L, P_R, \mathcal{R}} \ J_1 + J_2$$

s.t. $$0 \leq \mathcal{R}_i[l],$$

$$\sum_{l \in N_G} c_{G,i} (P_G[l] - P_G^i[l])^2 + \sum_{l \in E} c_{T,i} (\Delta T_i[l])^2$$

$$\forall l \in N_G$$

where

$$J_1 := \sum_{l=k}^{k+M} \left( \sum_{i \in N_G} c_{G,i} (P_G[l] - P_G^i[l])^2 + \sum_{l \in E} c_{T,i} (\Delta T_i[l])^2 \right)$$

and

$$J_2 := \sum_{l=k}^{k+M} c_{\mathcal{R},i} (\mathcal{R}_i[l])^2$$

As the risk-based MPC receives updated estimates at each time step, the cost of risk, $c_{\mathcal{R}}$, can be designed such that it penalizes risk early in the horizon and lowers the penalty later in the horizon. Larger $c_{\mathcal{R}}$ indicates higher cost and higher security and it is necessary to reach a good balance between risk of violation and nominal cost. To relate the value of improving tracking performance and the associated increase in operational risk, an efficient frontier for the tracking performance versus operational risk was computed by applying the weighting method in [33].

Also, similar to how line temperatures are driven below their limits, the MRC seeks to drive the SOC of VPPs below the robust bound. However, once below the robust bound, there is no risk-induced incentive to lower SOC further as shown in (15b) and (15c).

Figure 4 illustrates an example of the SOC of the VPP with respect to the estimated capacity of the VPP and its robust bound. The green circles highlight the points with zero added risk. On the other hand, the red circles demonstrate when the VPPs’ SOC is greater than the robust bound and takes on an increased, but weighted risk of DCS. The three explained methods can be summarized as follow:

I. The deterministic method dispatches VPPs with respect to the estimated SOC and energy capacity of VPPs.
II. The robust method dispatches VPPs with respect to the robust bound calculated with analytic reformulation.
III. The risk-based chance constrained (RB-CC) method co-optimizes reference-tracking performance and operational risk of DCS. Note that by sweeping $c_{\mathcal{R}}$ from $0 \to \infty$, the performance of the controller changes from the deterministic approach to the robust approach.

Remark V.1 Recall that unlike the existing literature on chance constrained optimization in power systems, this work considers the uncertainty of time-coupled energy variables on a fast time scale for corrective control.

VI. SIMULATION AND RESULT

In this section, the proposed control scheme in Fig. 1 is demonstrated on an augmented version of the IEEE RTS-96 power system test case, which includes three interconnected systems. The system is fully described in [34]. All optimization problems are solved in MATLAB and AMPL using the solver GUROBI. MPC employs the simplified linear model to compute all optimal control actions. However, the actual plant model is the non-linear AC system, with line temperature computed based on the non-linear thermodynamic IEEE Standard 738 conductor temperature model to accurately capture the effects of implementing MPC. The aim of this case study is to demonstrate generator reference-tracking performance with uncertain VPPs while considering physical constraints of the power system. Since the IEEE RTS-96 system is designed as a highly reliable system with high thermal ratings for lines. To push the system towards its limit and induce more congested scenarios, nominal thermal ratings are reduced by 40%, bringing line temperature limits in the range of $60-70^\circ$C. The network parameters are shown in Table I.

Initially, the system is at steady-state (i.e., generators following exactly an economic trajectory and VPP resources being available for balancing reserves). But at time $t = 5$ mins, the system experiences a net-load disturbance (e.g., forecasted net-load) that requires VPP balancing reserves to provide 10% reduction in the net-load (i.e., 855 MW) within 5 minutes, for at least 30 minutes to minimize unnecessary generators ramping. To evaluate the ability of the deterministic, robust, and RB-CC MPC formulations for the stochastic VPPs, 200 trials (i.e., realizations) are performed ($N_T = 200$) for four
TABLE I: Simulation Parameters

| Description          | Value |
|----------------------|-------|
| Number of buses      | 73    |
| Number of branches   | 120   |
| Number of generators | 96    |
| Total load           | 8550 MW |
| Number of VPPs       | 3     |
| Total capacity of VPPs | 855 MWh |
| VPPS bus ID (location) | 11,35,59 |
| VPP energy capacity  | 285 MWh |
| VPP initial SOC      | 50%   |
| Maximum VPP power    | 285 MW |
| VPPs ramp rate limit | 60 MW/min |
| Sampling time        | 60 s  |
| MPC prediction horizon | 20 mins |
| Avg. MPC solve time  | 3.19 sec |

TABLE II: VPP Uncertainty parameters

| Case       | σ₁ (%) | σ₂ (%) |
|------------|--------|--------|
| A (low/low)| 2      | 3      |
| B (high/low)| 5    | 3      |
| C (low/high)| 2    | 10     |
| D (high/high)| 5   | 10     |

Different scenarios of uncertainty as shown in Table II. The sum of squared tracking error of generators over the whole simulation time

\[ J_{Gen} := \sum_{m=1}^{N} \sum_{i\in N_G} (P_{G,i,m} - P_{G,i,m}^{ref})^2 \]  (16)

is used as the tracking MPC performance metric.

Since the deterministic approach dispatches VPPs without considering the second-order moment of the uncertainties, DCS happens more frequently. Mean squared tracking errors (MSTE) of generators for deterministic, robust, and RB-CC approaches under the different scenarios of uncertainty are shown in Fig. 5. Smaller MSTE implies better tracking performance. Poor performance of the deterministic approach is due to frequent occurrences of DCS. By applying the robust approach, chances of DCS is low, but since this method is conservative, the mean of objective under this method is still higher than RB-CC. Under RB-CC, the controller uses the available flexibility while considering the uncertainty and exceeds the robust bound only when it is most valuable to do so.

Histograms of the sum of the squared tracking error (\( J_{Gen} \)) of the deterministic, robust and RB-CC approaches for cases A, B, C, and D are shown in Fig. 6. Note that as expected, increasing the level of uncertainty makes the deterministic formulation susceptible to poor average performance while the robust and RB-CC formulations achieve similar performance.

To further investigate the effectiveness of the proposed method, the three large VPPs (one located in each region), are replaced by nine smaller VPPs (three located in each region) and location and parameters of small VPPs are shown in Table III. Intuitively, smaller VPPs should reduce the severity of DCS events, but increase their frequency.

TABLE III: Parameters for smaller VPPs

| Description            | Value |
|------------------------|-------|
| Number of VPPs         | 9     |
| Total energy capacity  | 855 MWh |
| Bus ID (location) of VPPs | 11,17,24,35,41,48,59,65,72 |
| VPP energy capacity    | 95 MWh |
| Initial VPP state of charge | 50% |
| Maximum VPP power output | 95 MW |
| VPPs ramp rate limit   | 20 MW/min |

The same analysis has been carried out on the system with the small VPPs and Case D (most sever uncertainty) results are shown in Fig. 7. Both robust and RB-CC approaches have shown better performance compared to the deterministic approach since they take uncertainty into account. However, the RB-CC method outperforms the robust method.

VII. CONCLUSIONS AND FUTURE WORKS

This paper studies the performance of a bi-level receding horizon predictive optimal power flow problem for managing variability with uncertain, flexible grid assets, such as VPPs. Since the SOC and capacity of VPPs can not be measured directly, a dynamic state estimator and simplified VPP aggregate model must be employed, which introduce uncertainty. This uncertainty in energy-constrained resources gives rise to the notion of dynamic capacity saturation (DCS). To overcome DCS, uncertainty can be managed by employing robust approaches. However, there is a sensitive trade-off between robustness of the optimized dispatch and closed-loop performance of the system. Indeed, robust approaches may lead to a conservative (high-cost) solution. Therefore, we introduced a RB-CC approach under
we are investigating stability guarantees for the MPC scheme and which the operational risk is optimized with respect to the dynamic states of the VPPs over a receding horizon. The numerical studies indicate that RB-CC outperforms other methods and significantly reduces DCS while maintaining good tracking performance.

Future work focuses on quantifying how well uncertain VPPs can regulate line temperatures under large disturbances. Furthermore, we are investigating stability guarantees for the MPC scheme and how uncertainty in the temperature estimates affects performance.

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