

Risk-Aware Stochastic Energy Management of Microgrid with Battery Storage and Renewables

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Abstract: This paper deals with optimization-based control of real microgrids with uncertain forecasts of renewable energy production and local consumption. To achieve maximum economic benefits, these uncertainties need to be accounted for in a systematic fashion. Conventionally, this task is approached by employing stochastic model predictive control. While doing so allows to account for uncertainties in the forecasts, the downside is high computational complexity that hinders implementation in real time. In this paper we therefore propose an alternative method that decreases the computational burden by an order of magnitude without inducing significant suboptimality. The approach is based on splitting the stochastic model predictive control problem into two stages, one that employs multiple realizations of the uncertainties combined with a low-fidelity prediction model, and one that uses only the risk-aware realization, combined with a high-fidelity model. The theoretical development is then showcased on a real microgrid to confirm viability of our approach.

Keywords: Predictive control; optimal operation and control of power systems; smart grids.

1. INTRODUCTION

The economic operation of microgrids with battery energy storage system (BESS) and renewable energy sources (RES) is a widely researched problem. The most attractive microgrid optimization technique is model predictive control (MPC). MPC draws attention due to its ability to predict the system's future behavior while satisfying predefined constraints. An overview and successful implementations of MPC in the microgrid are described in detail in the work of Hu et al. (2021). Since the power consumption and production forecasts included in a predictive controller are accompanied by uncertainty, implementation of the original so-called nominal or deterministic MPC approach can be insufficient. In order to explicitly include uncertainty in controller formulation with stability and recursive feasibility guarantees while satisfying the constraints, extensions to the MPC concept have been introduced. The most frequently used approaches are robust MPC (Bemporad and Morari (1999)), tube-based MPC (Mayne et al. (2006)), and stochastic MPC (Penad et al. (2006)).

To address the presence of uncertainty in our microgrid, we have decided to employ scenario-based stochastic model predictive control formulation as presented in Calafiore and Campi (2006) and Bernardini and Bemporad (2009). The scenario-based method delivers a single control sequence that incorporates different uncertainty realizations. The scenario-based approach was proposed in the work of Zhang et al. (2018), where two-stage microgrid control,

including prescheduling phase and real-time control, was carried out. The authors Casagrande and Boem (2022) have applied distribution techniques to reduce the computational burden. However, all of the proposed algorithms integrate one hour sampling time, which proved insufficient for today's application. Moreover, implementing a shorter sample time could yield time-consuming optimization problems.

Including risk measures into the stochastic optimization problems allows to adjust the controller according to given risk aversion. Risk measures such as value-at-risk (VaR) and conditional value-at-risk (CVaR) that originally come from financial portfolio management have recently been applied in the energy systems. In Wu et al. (2014) used CVaR measure to make a trade-off between the expected costs and the risk, but BESS output power was determined by fuzzy logic controller to exchange computation time for optimality. In studies Farzan et al. (2014); Ji et al. (2018); Shen et al. (2016), the risk-based approach for day-ahead scheduling of the microgrid was incorporated, but not for real-time control. In Khodabakhsh and Sirouspour (2016) was used CVaR directly in the objective of the rolling MPC, but with prediction intervals $N = 14$ and decisions updated every half and hour. Moreover, stated approaches were used only in simulations and lacks real-time control application in a realistic microgrid.

In this paper, we propose the MPC-based, risk-aware energy management system (EMS) for microgrids that

is applicable to real systems. The main contribution is developing a procedure capable of dealing with computation complexity arising from large-scale scenario MPC that allows using the predictive controller in real time. Designed EMS utilizes neural network-based forecasts to generate uncertainty scenarios for stochastic MPC.

The proposed methodology is based on a two-stage procedure. In the first step, a classic scenario-based MPC problem is solved with multiple scenario representations of the uncertainties and with a simpler prediction model. The result of this stage is the so-called CVaR-scenario, i.e., the scenario that corresponds to the desired CVaR level. Then, in the second stage, we solve another MPC problem, but this time with a single scenario identified previously, and with a high-fidelity model. In this way we can significantly reduce the computational time (up to ~ 50 -times) while still achieving a risk-aware control performance. These claims are validated by an experimental case study that employs a real industrial-grade microgrid.

2. ENERGY SYSTEM MODEL

2.1 Microgrid System

The considered microgrid system consists of photovoltaic (PV) power plant, battery energy storage, load demand and utility grid connection, see Fig. 1. Power production must match power consumption within the microgrid at each time $t \in [t_0, t_f]$, forming the power balance equation

$$P_{\text{imp}}(t) + P_{\text{PV}}(t) + P_{\text{dch}}(t) = P_{\text{exp}}(t) + P_{\text{ch}}(t) + P_{\text{load}}(t) + P_{\text{thr}}(t), \quad (1)$$

where all terms are non-negative. Production assets are on the left-hand side. Bi-directional flow with the grid is possible, $P_{\text{imp}}(t)$ denotes imported power for which the microgrid pays, $P_{\text{exp}}(t)$ denotes exported power for which the microgrid is paid. Power produced from the PV system $P_{\text{PV}}(t)$ can be predicted with some degree of uncertainty. If necessary, the PV inverter can be throttled, $P_{\text{thr}}(t)$ is the amount of dissipated energy. The load demand $P_{\text{load}}(t)$ is assumed to be inflexible. As with PV power, load demand can be predicted with some uncertainty. The battery storage serves as a power consumer when charging $P_{\text{ch}}(t)$ or as a power supplier when discharging $P_{\text{dch}}(t)$.

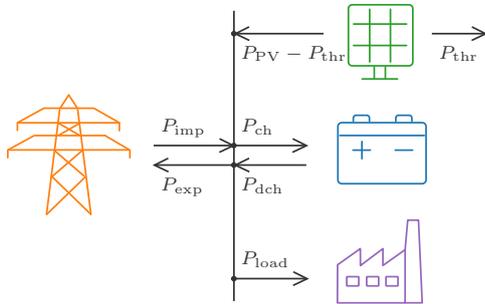


Fig. 1. Scheme of the microgrid system with power flows.

2.2 Battery Energy Storage

Battery storage system is modelled as an energy reservoir, whose state at time t is the current capacity level $E_{\text{bat}}(t)$. The system dynamics is described with the differential

equation where capacity level changes with the battery power (Ábelová and Kvasnica (2022))

$$\frac{dE_{\text{bat}}(t)}{dt} = -\sigma(E_{\text{bat}}(t)) + \eta_{\text{ch}} P_{\text{ch}}(t) - \frac{1}{\eta_{\text{dch}}} P_{\text{dch}}(t). \quad (2)$$

Some amount of energy is lost during the charging and discharging processes, the efficiencies are given by $\eta_{\text{ch}}, \eta_{\text{dch}} \in [0, 1]$. The self-discharging rate $\sigma(E_{\text{bat}}(t))$ can be regarded to the assumed time window neglected. The state is bounded by the minimum $\underline{\beta}$ and maximum $\bar{\beta}$ allowed state

$$\underline{\beta} E_{\text{bat}}^{\text{nom}} \leq E_{\text{bat}}(t) \leq \bar{\beta} E_{\text{bat}}^{\text{nom}}, \quad (3)$$

where $E_{\text{bat}}^{\text{nom}}$ is the nominal battery capacity and $\underline{\beta}, \bar{\beta} \in [0, 1]$. The maximum battery power is limited by $\bar{P}_{\text{ch}}, \bar{P}_{\text{dch}}$

$$0 \leq P_{\text{ch}}(t) \leq \bar{P}_{\text{ch}}, \quad (4a)$$

$$0 \leq P_{\text{dch}}(t) \leq \bar{P}_{\text{dch}}. \quad (4b)$$

If no additional constraints are imposed, stated model is linear and referred to as a relaxed model. If simultaneous charging and discharging is strictly prohibited, the non-linear complementarity constraint $P_{\text{ch}}(t) \cdot P_{\text{dch}}(t) = 0$ is added, or equivalent binary constraints as

$$0 \leq P_{\text{ch}}(t) \leq \delta_{\text{ch}}(t) \bar{P}_{\text{ch}}, \quad (5a)$$

$$0 \leq P_{\text{dch}}(t) \leq \delta_{\text{dch}}(t) \bar{P}_{\text{dch}}, \quad (5b)$$

$$\delta_{\text{ch}}(t) + \delta_{\text{dch}}(t) \leq 1, \quad (5c)$$

where $\delta_{\text{ch}}(t)$ and $\delta_{\text{dch}}(t)$ are binary variables.

3. METHODOLOGY

3.1 Method Outline

In conventional scenario-based stochastic MPC, the control actions are computed from a single optimization problem that accounts for multiple realizations of the uncertainties, but the number of scenarios negatively impacts the computational efficiency. To cut down the computational requirements, our method is based on the following procedure. First, we solve a scenario-based MPC with a low-fidelity prediction model and a longer sampling time. Such a problem can be solved quickly. Then we post-process the solution to identify the scenario that corresponds to the desired risk level. In the last step, we solve a deterministic MPC problem with the identified scenario, along with a high-fidelity prediction model and shorter sampling time. This way, we can yield control results faster compared to the conventional procedures.

3.2 Optimization Formulation

The energy management system of a microgrid is designed as a model predictive controller with the receding horizon strategy. The MPC computes decisions in discrete time intervals. The time horizon $[t_0, t_f]$ is split into N steps with sampling time $\Delta T(k) = t(k+1) - t(k)$, where $k \in \{0, \dots, N-1\}$ is the discrete time index. Note that time interval $\Delta T(k)$ is not restricted to be constant over the whole horizon.

Variables: The microgrid system model is described at the time step k with the state $\mathbf{x}(k)$, controls $\mathbf{u}(k)$, costs $\mathbf{c}(k)$, slacks $\mathbf{e}(k)$, weights $\mathbf{q}(k)$ and uncertainties $\mathbf{w}(k)$

$$\mathbf{x}(k) = [E_{\text{bat}}(k)], \quad (6a)$$

$$\mathbf{u}(k) = [P_{\text{ch}}(k), P_{\text{dch}}(k), P_{\text{thr}}(k), P_{\text{imp}}(k), P_{\text{exp}}(k)]^\top, \quad (6b)$$

$$\mathbf{c}(k) = [c_{\text{ch}}(k), c_{\text{dch}}(k), c_{\text{thr}}(k), c_{\text{imp}}(k), c_{\text{exp}}(k)]^\top, \quad (6c)$$

$$\mathbf{e}(k) = [\bar{\epsilon}_{\text{SoC}}(k), \underline{\epsilon}_{\text{SoC}}(k), \epsilon_{\text{imp}}(k), \epsilon_{\text{exp}}(k)]^\top, \quad (6d)$$

$$\mathbf{q}(k) = [\bar{q}_{\text{SoC}}(k), \underline{q}_{\text{SoC}}(k), q_{\text{imp}}(k), q_{\text{exp}}(k)]^\top, \quad (6e)$$

$$\mathbf{w}(k) = [P_{\text{PV}}(k), P_{\text{load}}(k)]^\top \quad (6f)$$

and all variables are defined over the whole horizon N to form vectors $\mathbf{X}^d, \mathbf{U}^d, \mathbf{C}^d, \mathbf{E}^d, \mathbf{Q}^d$ and \mathbf{W}^d .

The microgrid controller is to decide about optimal power setpoints for battery and PV inverters, and for power flow from or to the utility grid. Deterministic MPC considers only nominal forecasted values.

Constraints: Discrete battery model is derived from (2) as the first-order difference equation with sampling $\Delta T(k)$

$$E_{\text{bat}}(k+1) = E_{\text{bat}}(k) + \Delta T(k) \left(\eta_{\text{ch}} P_{\text{ch}}(k) - \frac{1}{\eta_{\text{dch}}} P_{\text{dch}}(k) \right). \quad (7)$$

State of charge limits (3) are formulated as soft constraints with slacks $\bar{\epsilon}_{\text{SoC}}, \underline{\epsilon}_{\text{SoC}}$ penalization

$$E_{\text{bat}}(k) \leq \bar{\beta} E_{\text{bat}}^{\text{nom}} + \bar{\epsilon}_{\text{SoC}}(k), \quad (8a)$$

$$E_{\text{bat}}(k) \geq \underline{\beta} E_{\text{bat}}^{\text{nom}} - \underline{\epsilon}_{\text{SoC}}(k). \quad (8b)$$

Power balance constraint (1) is complemented with limits

$$P_{\text{thr}}(k) \leq P_{\text{PV}}(k), \quad (9a)$$

$$P_{\text{imp}}(k) \leq \bar{P}_{\text{imp}} + \epsilon_{\text{imp}}(k), \quad (9b)$$

$$P_{\text{exp}}(k) \leq \bar{P}_{\text{exp}} + \epsilon_{\text{exp}}(k). \quad (9c)$$

All stated slacks are non-negative. The grid limits \bar{P}_{imp} and \bar{P}_{exp} represents not physical, but rather contractual, agreed upon thresholds, whose overreaching is penalized.

Objective: The purpose of the energy management system is to maximize profit while ensuring smooth operation. The microgrid benefits from PV utilization, price arbitrage when electricity tariff differs, and from selling the energy. The microgrid is charged for importing energy, using the battery storage, and violating grid limits. The objective function that captures mentioned yields and costs is

$$J(\mathbf{x}(0), \mathbf{U}^d, \mathbf{C}^d, \mathbf{E}^d, \mathbf{Q}^d, \mathbf{W}^d) = \sum_{k=0}^{N-1} \left(\Delta T(k) \mathbf{u}(k)^\top \mathbf{c}(k) + \mathbf{e}(k)^\top \mathbf{q}(k) \right). \quad (10)$$

Objective minimizes total costs subjected to the battery state model, initial conditions, state and control boundaries, where boundary sets \mathcal{X}, \mathcal{E} are function of slack vector \mathbf{E}^d to ensure the solution is feasible under any condition

$$\min_{\mathbf{x}^d, \mathbf{U}^d, \mathbf{E}^d} J(\mathbf{x}(0), \mathbf{U}^d, \mathbf{C}^d, \mathbf{E}^d, \mathbf{Q}^d, \mathbf{W}^d) \quad (11a)$$

$$\text{s.t. } \mathbf{x}(k+1) = f(\mathbf{x}(k), \mathbf{u}(k)), \quad \forall k, \quad (11b)$$

$$\mathbf{x}(0) = x_0, \quad (11c)$$

$$\mathbf{w}(0) = w_0, \quad (11d)$$

$$\mathbf{X}^d \in \mathcal{X}(\mathbf{E}^d), \quad (11e)$$

$$\mathbf{U}^d \in \mathcal{U}(\mathbf{E}^d, \mathbf{W}^d), \quad (11f)$$

$$\mathbf{E}^d \in \mathbb{R}_{\geq 0}. \quad (11g)$$

Using the receding horizon strategy, the MPC outputs optimal control sequence \mathbf{U}^{d*} for the whole prediction horizon from which the first control vector $\mathbf{u}(0)^*$ is applied for time $\Delta T(0)$ and procedure is repeated at $k+1$ with new state measurement x_0 and uncertainty vector \mathbf{W}^d .

3.3 Forecasting and Scenario Generation

The uncertainty $\mathbf{w}(k)$ of the system disturbances is modeled as point prediction with additional confidence bounds within the real value can vary. Both of these information needs to be provided at each step of the horizon N .

Load demand: For the electricity load demand, the seasonal autoregression model is considered. This model is a sufficient tool for forecasting stochastic processes with seasonal aspects (Guefano et al. (2021)). The point predictions are calculated as a linear dependence from the past sequences

$$\hat{P}_{\text{load}}(k) = \sum_{j=1}^R \gamma_j P_{\text{load}}(k - r_j), \quad (12)$$

where vector r is a set of seasonal repetitions on which $\hat{P}_{\text{load}}(k)$ is regressed on, and γ_j represents a regression coefficient for define historical value $P_{\text{load}}(k - r_j)$.

A simple but accurate method is used to construct a confidence interval. As the minimal and maximal value which can occur is one of the correlated historical values, then the confidence interval can be formulated as follows

$$\left[\begin{array}{c} P_{\text{load}}^{\text{ub}}(k) \\ P_{\text{load}}^{\text{lb}}(k) \end{array} \right] = S_f \left[\begin{array}{c} \max(P_{\text{load}}(k - r_1), \dots, P_{\text{load}}(k - r_R)) \\ \min(P_{\text{load}}(k - r_1), \dots, P_{\text{load}}(k - r_R)) \end{array} \right], \quad (13)$$

where S_f is and scaling factor, $P_{\text{load}}^{\text{ub}}(k)$ is a upper, and $P_{\text{load}}^{\text{lb}}(k)$ is a lower bound of the confidence interval.

PV production: In the case of power production from the photovoltaic panels, recurrent neural network (RNN) shows excellent performance for short and medium-term horizons (Rodríguez et al. (2018)). Moreover, the RNN is trained as standard regression to minimize mean square error. In conclusion, RNN is a non-linear prediction model based on weather forecasts for the exact location of the PV panels

$$\hat{P}_{\text{PV}}(k) = f_{\text{PV}}(z(k)), \quad (14)$$

where f_{PV} represents trained model, and $z(k)$ is a weather forecast for corresponding time index k .

The confidence interval is calculated using the maximum likelihood method (Nix and Weigend (1994)). This approach assumes that the distribution of the variable of interest can be divided into two separate parts, expected value $\hat{P}_{\text{PV}}(k)$ and the noise. With this assumption, it is possible to estimate total prediction variance $\sigma^2(k)$ directly, including the model uncertainty and the measurement noise. The main idea of this approach is to build a second RNN

$$\hat{\sigma}^2(k) = f_\sigma(z(k)), \quad (15)$$

which estimates total variance $\hat{\sigma}^2(k)$ of the given prediction $\hat{P}_{\text{PV}}(k)$ with the identical input $z(k)$ as in the point prediction model from (14). The final confidence interval is defined in this form

$$\begin{bmatrix} P_{PV}^{\text{ub}}(k) \\ P_{PV}^{\text{lb}}(k) \end{bmatrix} = \begin{bmatrix} \hat{P}_{PV}(k) + S_f \sqrt{\hat{\sigma}^2(k)} \\ \hat{P}_{PV}(k) - S_f \sqrt{\hat{\sigma}^2(k)} \end{bmatrix}, \quad (16)$$

where $P_{PV}^{\text{ub}}(k)$ is an upper, and $P_{PV}^{\text{lb}}(k)$ is a lower bound of the confidence interval.

Scenario generation: The proposed scenario generation method is based on a multi-step procedure with two random variables, assuming that the uncertainty of the system disturbances comes from Gaussian distribution.

- (1) Calculate the point prediction $\hat{\mathbf{w}}(k)$, and confidence interval $[\mathbf{w}^{\text{ub}}(k), \mathbf{w}^{\text{lb}}(k)]^\top$ for each step of the prediction horizon N .
- (2) Generating random variable $\omega_\beta \sim \mathcal{N}(\mu, \sigma_\beta^2)$, where $\sigma_\beta^2 = (1 - \mu) \frac{\exp(\beta/100)^2/2}{\sqrt{2\pi}}$. This variable ω_β is scaled in such a way that $(100\% - \beta)$ represents how many scenarios will be generated outside of the confidence interval $[\mathbf{w}^{\text{ub}}(k), \mathbf{w}^{\text{lb}}(k)]^\top$, with $\mu = 0.5$.
- (3) Generate the additional random variable in each time step k which behaves like a white noise $\omega_n(k) \sim \mathcal{N}(0, \sigma_n^2(k))$, where $\sigma_n^2(k)$ is calculated from the historical data. This way, it is possible to mimic real noise acting on the system but still hold the Gaussian distribution for the generated scenario.
- (4) The final scenario is produced as follows

$$\mathbf{w}(s, k) = \omega_\beta \mathbf{w}^{\text{ub}}(k) + (1 - \omega_\beta) \mathbf{w}^{\text{lb}}(k) + \omega_n(k), \quad (17)$$

where s represents an index of the generated scenario.

This procedure is repeated for the desired number of scenarios. It is important to note that scenario generation is independent of the method employed for the point prediction and its respective confidence bounds.

3.4 Stochastic Model Predictive Control

When introducing scenarios, dimension of all variables is expanded with scenario index $s \in \mathcal{S}$, where set $\mathcal{S} = \{1, \dots, N_S\}$ and N_S is the number of scenarios, define vectors $\mathbf{X}^s(s)$, $\mathbf{U}^s(s)$, $\mathbf{C}^s(s)$, $\mathbf{E}^s(s)$, $\mathbf{Q}^s(s)$ and $\mathbf{W}^s(s)$.

Every scenario trajectory in the uncertainty vector $\mathbf{W}^s(s) = [\mathbf{w}(s, 0), \mathbf{w}(s, 1), \dots, \mathbf{w}(s, N-1)]^\top$ is created according to the scenario generation strategy. Variables $\mathbf{X}^s(s)$, $\mathbf{U}^s(s)$, and $\mathbf{E}^s(s)$ are optimized for every scenario, while costs $\mathbf{C}^s(s)$ and weights $\mathbf{Q}^s(s)$ are considered constant.

Because of decisions at $k = 0$ are based on the same past information and $\mathbf{w}(s, 0) = w_0$, $\mathbf{x}(s, 0) = x_0$ for all $s \in \mathcal{S}$, it is possible to introduce non-anticipatory constraints (Velarde et al. (2017)), which are necessary to compute control $\mathbf{u}(s, 0)^*$ that is equal for all the scenarios in the first time step

$$\mathbf{u}(i, 0) = \mathbf{u}(j, 0) \quad \text{if} \quad \mathbf{w}(i, 0) = \mathbf{w}(j, 0); \quad \forall i \neq j, \quad (18)$$

where $i, j \in \mathcal{S}$.

A robust controller would make decisions regarding the worst-case predictions leading to the too conservative control. Desired behaviour of the controller is to consider uncertainties, but not to be overly reserved in the actions. Incorporating probabilistic risk measure such as value at risk allows to adjust a degree of risk aversion. If $C(s)$ is the cost distribution, VaR with α -percentile is defined as

$$\text{VaR}_\alpha \triangleq \min\{c \in \mathbb{R} : \mathcal{P}\{C(s) \leq c\} \geq \alpha\}, \quad (19)$$

where \mathcal{P} denotes the probability of the cost $C(s)$ not exceeding the threshold cost c . VaR can be interpreted as the maximum cost that will not be exceeded with the probability $(1 - \alpha)$. VaR drawback that it is a non-coherent risk measure lacking convexity properties can be avoided by including conditional value at risk variable (Khodabakhsh and Sirouspour (2016)). CVaR expresses the expected value of the worst $(1 - \alpha)$ -quantile of the cost distribution

$$\text{CVaR}_\alpha \triangleq \mathbb{E}[C(s) | C(s) \geq \text{VaR}_\alpha]. \quad (20)$$

Using the linearized formulation of CVaR introduced by Rockafellar et al. (2000) it is possible to minimize the risk measure in the form

$$\text{CVaR}_\alpha = y + \frac{1}{1 - \alpha} \sum_{s=1}^{N_S} \pi(s) [C(s) - y]^+, \quad (21)$$

y represents VaR_α , $\pi(s)$ is the probability of the scenario s , $C(s) = J(\mathbf{x}(s, 0), \mathbf{U}^s(s), \mathbf{C}^s(s), \mathbf{E}^s(s), \mathbf{Q}^s(s), \mathbf{W}^s(s))$ is the cost of the scenario s , and $[C(s) - y]^+ = (C(s) - y)$ if $(C(s) - y) > 0$, else $[C(s) - y]^+ = 0$. With the auxiliary variable $z(s)$ defined as

$$z(s) \triangleq \max(0, (C(s) - y)), \quad (22)$$

it is possible to formulate optimization problem minimizing CVaR_α as

$$\min_{y, C, z} \left(y + \frac{1}{1 - \alpha} \sum_{s=1}^{N_S} \pi(s) z(s) \right) \quad (23a)$$

$$\text{s.t.} \quad z(s) \geq C(s) - y, \quad \forall s, \quad (23b)$$

$$z(s) \geq 0, \quad \forall s. \quad (23c)$$

Deterministic MPC stated in (11) is expanded with scenarios and objective is replaced with CVaR_α measure in the form (23a) to formulate stochastic MPC as follows

$$\min_{\mathbf{x}^s, \mathbf{U}^s, \mathbf{E}^s, y, z} \text{CVaR}_\alpha \quad (24a)$$

$$\text{s.t.} \quad \mathbf{x}(s, k+1) = f(\mathbf{x}(s, k), \mathbf{u}(s, k)), \quad \forall s, \forall k, \quad (24b)$$

$$\mathbf{x}(s, 0) = x_0, \quad \forall s, \quad (24c)$$

$$\mathbf{w}(s, 0) = w_0, \quad \forall s, \quad (24d)$$

$$\mathbf{X}^s(s) \in \mathcal{X}(\mathbf{E}^s(s)), \quad \forall s, \quad (24e)$$

$$\mathbf{U}^s(s) \in \mathcal{U}(\mathbf{E}^s(s), \mathbf{W}^s(s)), \quad \forall s, \quad (24f)$$

$$\mathbf{E}^s(s) \in \mathbb{R}_{\geq 0}, \quad \forall s, \quad (24g)$$

$$(18), (23b), (23c). \quad (24h)$$

3.5 Double-Stage α -Scenario MPC

Solving multiple-scenario optimization problem is computationally demanding as the computational complexity grows with the number of scenarios. This time barrier may hinder deployment in the real energy systems. If all generated scenarios could be reduced to α -scenario s_α whose cost $C(s_\alpha)$ is equal to CVaR_α value, MPC can be solved as a deterministic problem with advantages of stochastic MPC. The proposed MPC-based energy management system solves optimization problem twice in separate stages and the whole procedure consists of the following steps:

- (1) Get initial conditions x_0, w_0 , set $k \leftarrow k + 1$.
- (2) Generate N_S scenarios with normal distribution from the given upper and lower bounds of the confidence interval to obtain the uncertainty vector \mathbf{W}^s . Update $\mathbf{w}(s, k) = w_0$, $\forall s$ with the initial condition.

- (3) Solve stochastic MPC (stage 1) stated in (24) for N_S scenarios with the prediction model of the form (4) that does not account for nonlinear complementarity constraints. Use the longest sampling time the system allows to reduce the number of prediction intervals N .
- (4) Select scenarios s with cost $C(s) \geq \text{VaR}_\alpha$ to obtain the subset $\mathcal{S}_\alpha \subset \mathcal{S}$. Number of selected scenarios, $|\mathcal{S}_\alpha| = (1 - \alpha) \cdot N_S$ and expected cost $\mathbb{E}[C(s)] = \text{CVaR}_\alpha$ for $s \in \mathcal{S}_\alpha$. Calculate weighted average α -scenario s_α with cost $C(s_\alpha) = \text{CVaR}_\alpha$.
- (5) Solve deterministic MPC (stage 2) stated in (11), where $\mathbf{W}^d = \mathbf{W}^s(s_\alpha)$. Use the high-fidelity prediction model with nonlinear complementarity constraints (5). Use variable sampling time with shorter intervals.
- (6) Extract optimal control setpoint $\mathbf{u}(k)^*$ from the solution and apply it for the whole $\Delta T(k)$.
- (7) Move to $t(k) + \Delta T(k)$ and repeat from step 1.

Block diagram of procedure steps is shown in Fig. 2.

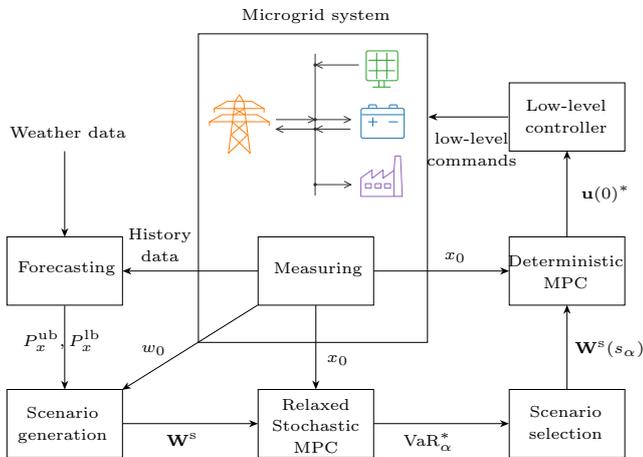


Fig. 2. Diagram of the proposed procedure with data flows.

4. CASE STUDY

The proposed control system is implemented for the EV charging station with photovoltaic system and battery energy storage. The PV system of size 150 kWp and 100 kW inverter is oversized for the station's load demand, with a workday daily average below 10 kW. The battery storage rated 50 kW/151 kWh was installed to supplement photovoltaic system to enhance overall microgrid energy management. The site has a utility grid connection and may feed-in excessive energy, however, the export prices are lower than import prices. The grid operator provides dual electricity tariff, creating a space for price arbitrage.

With the deterministic MPC ignoring forecast errors the often seen behaviour was that the battery state wasn't well prepared for the upcoming events. If PV production was delayed or a vehicle was plugged in earlier than predicted, the storage was already empty and microgrid had to import power. Or if PV production exceeds expectations, the battery didn't have enough space for storing excessive energy. The risk-averse control strategy is not aiming for the best possible outcome when the forecasts come true (rarely), but for optimal outcome when they does not. With the CVaR optimization we could be $\alpha \cdot 100\%$ sure that expected cost will not exceed value VaR_α .

4.1 Implementation

The proposed energy management system utilizing risk-aware α -scenario MPC was implemented using Pyomo modelling framework and both, the relaxed LP and MILP problem were solved using GLPK solver.

Both forecasting models were trained using more than six months of historical data. In the case of electricity consumption (12), seasonal repetition r consists of historical measurements from 1-4 weeks. PV production (14) depended on weather forecasts of humidity, temperature, irradiance, and cloud base. The structure of this model was selected as RNN with 40 long short-term memory units. Confidence intervals were scaled with 90% certainty.

For the stochastic MPC, risk parameter $\alpha = 20\%$ and the prediction horizon was 1 day with 15 min sampling, $N = 96$, and $N_S = 50$. The subsequent deterministic MPC in the second stage of procedure used variable sampling time $\Delta T(k) = 1$ min for $k \in \{0, \dots, 14\}$, $\Delta T(k) = 5$ min for $k \in \{15, \dots, 23\}$, and $\Delta T(k) = 15$ min for $k \in \{24, \dots, 115\}$.

4.2 Numerical Results

Closed-loop control: Weather forecasts and thus PV production forecasts are updated every hour. Fig. 3 shows confidence intervals and generated scenarios predicted at midnight. During the microgrid operation, the low-level controller requested a new setpoint every 60 s, valid for 120 s. If MPC solver does not converge, last setpoint is used if valid, $P_{\text{ch}} = P_{\text{dch}} = 0$ otherwise. Results of the closed-loop control are shown in Fig. 4. The battery is charging from the grid during the night lower electricity tariff to have enough energy for supply until PV plant starts to produce. Then battery stores excessive PV energy to cover load demand later. PV system produced 150.1 kWh/day from which 90.9% was utilized for self-consumption. Energy consumption of the microgrid was 137.8 kWh/day of which 77.0 kWh had to be imported from the utility grid.

Comparison: An open-loop simulations of the regular stochastic MPC (Subsection 3.4) and double-stage α -scenario MPC (Subsection 3.5) were performed to compare control strategies under the same conditions. The evaluations of the worst-case solving time and scaled objective value are in Table 1. The regular stochastic MPC includes complementarity constraints and variable sampling time, so does the MPC problem in the second stage of α -scenario MPC. Tests were run on M1 8-core chip, 8 GB RAM. The double-stage α -scenario MPC can find a solution up to ~ 50 -times faster with just a modest suboptimality.

Table 1. Performance comparison

Method	Solving time	Objective value
Stochastic MPC	1605.1 s	1.00
Double-stage MPC	27.4 s	1.05

5. CONCLUSION

We have presented the control strategy for microgrids and the application for the real system. The proposed MPC scheme is able to handle uncertainties arising from the prediction errors of power consumption and production.

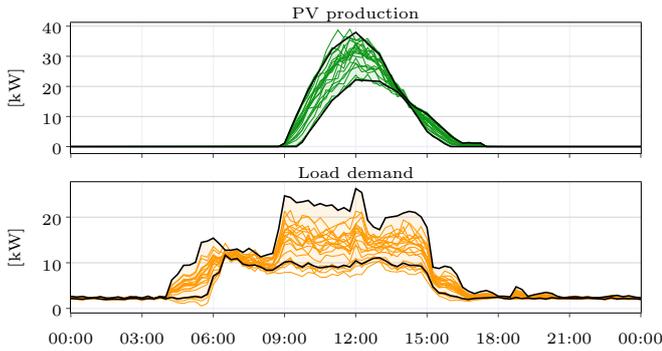


Fig. 3. 20 scenario trajectories of PV production and load demand generated from forecasted 90% confidence intervals, upper and lower bounds indicated in black.

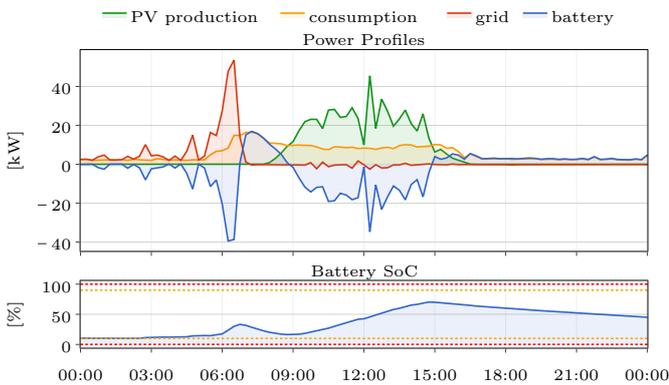


Fig. 4. Realized power flows in the microgrid. In the upper plot, battery charging and grid exports values are shown as negative.

In the case study, the grid import and export prices were precisely known beforehand, but the framework allows to consider any uncertainties. Using stochastic optimization with multiple scenarios of uncertainty trajectories to find optimal control decisions is time-consuming, what had to be overcome in the real application. The proposed approach can deal with the complexity and still decide optimal setpoints regarding adjustable risk parameter. The results of applying the proposed control strategy in the microgrid showed desired control behaviour.

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