ATTEST PROJECT: TOOLS FOR ANCILLARY SERVICE PROCUREMENT IN DAY-AHEAD OPERATION AND REAL-TIME ACTIVATION IN DISTRIBUTION GRIDS

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ABSTRACT

The efforts to achieve carbon-neutral power systems aim to reduce the harmful effects of greenhouse gas emissions on climate. The energy systems of 2030 and beyond will face an increasing need for flexibility and generation back-up capacity in order to accommodate massive penetration of renewable energy sources (RES) together with the electrification of transport, heating and cooling sectors. In line with these changes, this paper describes two innovative tools developed in ATTEST project, that focus on the optimal procurement of ancillary services (AS) in day-ahead operation planning and optimal activation of AS in real-time operation of distribution grids. Specifically, these tools compute at the two different stages optimal settings of a variety of distributed energy resources namely: RES, battery storage units, shiftable (flexible) loads, particularly electric vehicles, and grid control means such as On-load Tap Changing (OLTC) transformers. The tools have been successfully tested on a variety of realistic models of distribution grids from UK, Croatia, Portugal and Spain.

INTRODUCTION

With the latest package of measures towards carbon-neutral power system *Fit for 55*, Europe set an ambitious goal in becoming carbon neutral by 2050 with higher targets in greenhouse gas emission reduction, increased share of renewable energy resources (RES) in total energy mix and increased improvements of energy efficiency [1]. In line with this, new sources of flexibility in power system are necessary to ensure secure and efficient system operation for both transmission and distribution grids.

Distribution grids can face major operation issues at high penetration of variable RES, such as over/under-voltages or congestion that require new solution approaches for alleviation. For example, to mitigate the effects of wind power uncertainty, the optimization model in [2] proposes flexibility service provision from a Fast Charging Station of Electric Vehicles (EVs) equipped with Distributed Energy Resources (DERs). Providing flexibility in a two-stage Active Distribution Network management model is described in [3]. The first stage is modelled with a linearized dynamic optimal power flow model considering power set-points of DERs flexibility curves and uncertainties related to the demand profile and RES production. The second stage in real-time (RT) operation controls battery storage in order to reduce the imbalances at the point of common coupling between distribution and transmission network. A local flexibility three-stage market design was proposed in [4] under the project FLEXIMAR for local voltage control and congestion management, but also for frequency containment reserve. In the first stage pre-matching process of flexible capacities matching bids and offers is achieved with a goal of social welfare maximization. The second stage checks the feasibility of local bids in order to prevent security constraints violation. In the last stage offers are accepted based on the amount obtained from the second stage. DERs participation in energy and flexibility market through aggregator is modelled in [5] considering exchanged power at the point of common coupling with transmission network and uncertainties related to the energy prices, PV production and load. The robust optimization results in optimal strategic bidding which satisfies obligation from DA and flexibility markets. A local decentralized flexibility market operated by the DSO in order to purchase flexibility needs when the maximum demand limits are violated is presented in [6].

Congestion management in distribution network can be employed through distribution local marginal pricing mechanism [7]–[10], dynamic tariff method [11] and dynamic subsidy method [12]. Voltage control in distribution network is divided in four groups: local, decentralized, distributed and centralized [13]. In local voltage control the decisions are made based on the local measurements of voltage and currents, while the voltage control is established through reactive power control of DERs, active power curtailment or load control. In decentralized control coordination of various system components is achieved without the regulation from the system operator. Distributed control implies node-local computation without a central controller. In centralized control state estimation is used for estimating the voltage profiles based on the DERs dispatchment. This type of control allows optimized operation of the entire region through a coordinated control of OLTC, DERs and voltage regulators. A two-level RT voltage control in [14] is divided in local and centralized control of distributed generation units. The local control implies providing fast response when the contingency occurs trying to reduce the impact of the contingency and at the same time to improve the voltage quality, while the centralized control is focused on balancing generation and bringing the voltage in the allowed limits using model predictive control.

ATTEST project [15] focuses on the development of a platform for a coordinated planning and operation of distribution and transmission networks of 2030 and beyond. This paper describes two operation tools being developed in the project for ancillary services (AS) procurement in day-ahead (DA) operation planning and RT activation in the distribution network. The tool for flexibility procurement for voltage control and congestion management in DA operation planning of the distribution network supports the Distribution System Operator (DSO) in mitigating RES uncertainty and ensuring that the network capacity is never exceeded in RT operation. The tool for AS activation in RT operation of the distribution network optimizes the activation of flexibility provided from DSO assets or procured from the AS market aiming to maintain the safe distribution network operation. Both tools consider Transmission System Operator (TSO)/DSO coordination mechanism which is crucial for avoiding procurement and activation of counteracting services from resources connected to the distribution network.

TWO-STAGE ATTEST SOLUTION FOR ANCILLARY SERVICES PROCUREMENT AND ACTIVATION IN DISTRIBUTION GRIDS

Figure 1 shows the two-stage coupled management of AS in distribution grids, proposed in the ATTEST project, including input data and interaction of the tools together with the DA and RT TSO-DSO coordination. In DA AS procurement due to the complexity of pricing mechanism, active and reactive flexibility bids are procured separately, while in RT both active and reactive bids are activated simultaneously. An interested reader is referred to [16] for detailed description of TSO/DSO coordination mechanism developed in ATTEST project.

DA tool receives flexibility bids from DERs, network data together with scenarios of RES production and load and potentially requests from the TSO for AS provision in the transmission network, which serve as an input data in the model.

DA tool sends the optimal set-points of DERs to the RT tool together with up and down limits for providing flexibility service for each DERs. RT tools re-dispatches DERs setpoints based on the state-estimation results in order satisfy the distribution network constraints and to provide the required flexibility to the TSO.

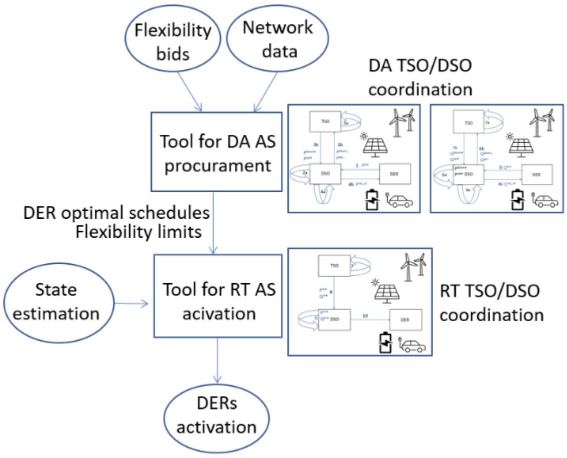

Figure 1 Tools for DA procurement and RT activation of AS in distribution grid

DAY-AHEAD ANCILLARY SERVICE PROCUREMENT IN DISTRIBUTION GRIDS

The procurement of ancillary services for voltage control and congestion mitigation in medium voltage distribution grids is formulated as a centralized stochastic multi-period AC optimal power flow (S-MP-OPF) problem [17]. The stochasticity of RES (e.g. wind/solar) power production is modelled by a set of s independent scenarios generated using time-series based auto-regressive integrated moving average (ARIMA) model [18]. The problem can be formulated in an abstract way as follows:

$$\min f(u_{s,t}) \tag{1}$$

$$g_{s,t}(u_{s,t}, x_{s,t}) = 0 \tag{2}$$

$$h_{s,t}(u_{s,t}, x_{s,t}) \leq 0 \tag{3}$$

where, for every RES uncertainty scenario s and period of time t (without loss of generality, 24 hours ahead are generally modelled with a time resolution of one hour), $u_{s,t}$ denotes the vector of control variables or flexible options (e.g. RES active and reactive power, OLTC ratio, state of charge of storage units, power demand of flexible loads such as EVs), $x_{s,t}$ represents the vector of state variables (i.e., real and imaginary parts of complex voltage at nodes), the objective (1) minimizes the expected cost of grid operation, equality constraints (2) express active and reactive power balance at nodes and constraints (3) include operation limits (e.g. on bus voltage magnitudes and currents through branches) as well as physical or operation limits on DER (e.g., active/reactive power range of RES, energy intertemporal constraints modelling the operation of storage and flexible loads including their energy conservation, and limits on OLTC ratio).

The full-flexibility options model above is a mixed-integer nonlinear programming (MINLP) problem; however, some combinations of flexible options (e.g., adjustments of RES active/reactive power or OLTC ratio) lead to simpler NLP problems.

The S-MP-OPF model has been developed in Julia/JuMP [19], [20] environment. For benchmarking purposes, the models are first solved via off-the-shelf solvers such as IPOPT (when NLP) or Bonmin (when MINLP). Then, for the sake of tractability, the proposed tool itself relies on successive linearizations of the MINLP problem, through MILP models, whose accuracy is iteratively improved. The proposed linearization employs second-order Taylor series expansion of trigonometric terms in the nonlinear constraints in (2), i.e., the active/reactive power flows, and (3), i.e., the branch currents [21]. As such the MILP models are formulated in variables such as square of voltage magnitude and voltage angle difference between nodes. The tool has been tested on several different datasets and provides systematically highly accurate solutions in acceptable computation time (i.e., at most a few minutes).
The objective function considered in the DA tool minimizes the overall cost of the network operation, which consists of the expected cost associated with the DER deviation from the market schedule in each scenario s and time-period t:

$$\min\sum_{s\in S}\sum_{t\in T}\pi_s\Big\{\Big(\sum_{i\in G}c_{i,p}^{curt}P_{i,s,t}^{curt}+\sum_{i\in B}c_{i,b}^{str}(P_{i,s,t}^{dch}-P_{i,s,t}^{ch})+ c_{i,l}^{fl}\sum_{i\in F}(P_{i,s,t}^{od}+P_{i,s,t}^{ud})\Big)\Delta T+c_{ij}^{oltc}|\alpha_{ij,s,t}-\alpha_{ij,s,t}^{0}|\Big\}$$

where P_i^{curt}, is the curtailed active power of RES unit, P_i^{dch} and P_i^{ch} are the active power discharging and charging of battery storage unit, and P_i^{od} and P_i^{ud} are the active power overdemand and underdemand of flexible load.

Figures 2 and 3 show some typical results obtained with this tool as regards optimal redispatch of a particular type of flexible load, namely the modulation of EV charging and discharging, at two locations termed FL:7 and FL:29, with respect to their desired pattern and while fulfilling their energy balance on 24 hours. One can observe an expected behaviour as: (i) under-demand (i.e., reduction of demand/EV charging occurs mostly) at peak load in the evening, where the grid is highly loaded and (ii) over-demand (i.e., increase in demand/EV charging) happens mainly at night or around noon, when the load is light while wind and PV production is high.

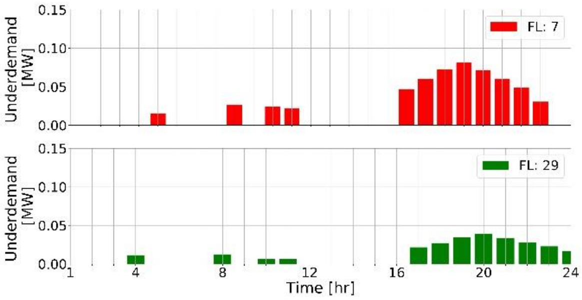

Figure 2 Under-demand of two flexible loads

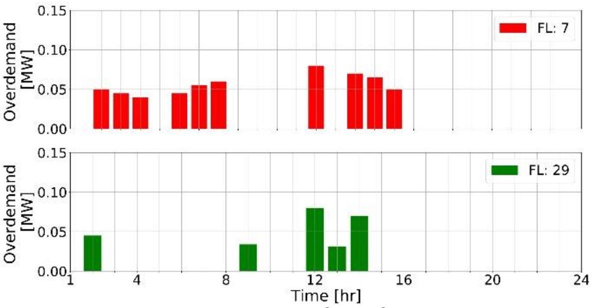

Figure 3 Over-demand of two flexible loads

Finally, the optimal scheduling of DERs obtained upon solving the S-MP-OPF problem (1)-(3) are transmitted to the RT tool for activation of AS, which is described below.

REAL-TIME ANCILLARY SERVICE ACTIVATION IN THE DISTRIBUTION NETWORK

The RT tool determines optimal flexibility activation procured by both system operators. The activation aims to optimally re-dispatch DER setpoints, with respect to their optimal values procured in DA stage by the previous tool, so as to remove distribution network operating constraint violations at minimal cost and to provide requested flexibility by the TSO for the transmission network.

The mathematical foundation is set in exact AC OPF formulation in rectangular coordinates. Equations (4) and (5) describe power flow formulas. The rectangular notation is of nonconvex quadratically constrained quadratic programming (NC-QCQP) form which offers computational benefits as opposed to the polar notation which belongs to general nonlinear programming form. Normally, nonlinear solvers at every solver iteration request from the solver-calling program or programming language to evaluate nonlinear functions, Jacobian and Hessian matrices. However, since NC-QCQP is quadratic, it has constant Hessian matrix which thus does not need to be recomputed which speeds up computation. This is relevant since this tool works in RT. Of the high relevance is also that there are no discrete variables in the model. Activation of all flexible sources in either up or down direction is costly so the simultaneous up and down flexibility activation never occurs even without binary variables to prevent this. Discrete variables are generally known to be computationally the most demanding component of optimizations.

$$P_{n,m}=g\cdot\left((V_n^d)^2+\left(V_n^q\right)^2\right)-g\cdot\left(V_n^dV_m^d+V_n^qV_m^q\right) +b\cdot\left(V_n^dV_m^q-V_n^qV_m^d\right) \quad (4)$$

$$Q_{n,m}=-b\cdot\left((V_n^d)^2+\left(V_n^q\right)^2\right)+b\cdot\left(V_n^dV_m^d+V_n^qV_m^q\right) +g\cdot\left(V_n^dV_m^q-V_n^qV_m^d\right) \quad (5)$$

$P_{n,m}$ and $Q_{n,m}$ are active and reactive power flow variables, V^d and V^q are real and imaginary part of voltages, while b is susceptance of the line nm and g represents conductance of the line.

The tool receives input data from two other tools: the DA reserve procurement tool and from the distribution network state estimation also developed within the project. The procurement tool data includes flexible source limits and costs. There are 3 flexibility source categories: loads, distributed generators and storage units. Loads provide demand response manifested as overdemand or underdemand, generators can be curtailed and storage units can provide both up and down, active and reactive power services. State estimation tool computes distribution network state from measurement data: voltage magnitudes and angles, power flows and bus injections. Standardized MATPOWER data format is used to exchange state estimation between the tools and to store distribution network data, but custom Excel-based format for flexibility sources data.

Tackling uncertainties is important in power system plaining due to high electricity value of loss load. This is especially difficult in RT optimization where computation time is limited and prediction models need to be simple. This RT tool works in model predictive control (MPC) fashion shown in Figure 4. It optimizes for the present and several near future time periods. Future time periods are based on two prediction scenarios, one for the high load and the other for low load. High load scenario simply multiplies all current loads with time-progress increasing factor, and low load scenario with time-progress decreasing factor. For storage, the tool tracks state-of-energy changes to avoid requesting infeasible flexibility activation due to storage depletion or overcharge. The MPC approach makes the optimization conservative, i.e., it may not activate flexibility sources at the fullest or even the least expensive in the present so that it is better prepared for potentially even worse future.

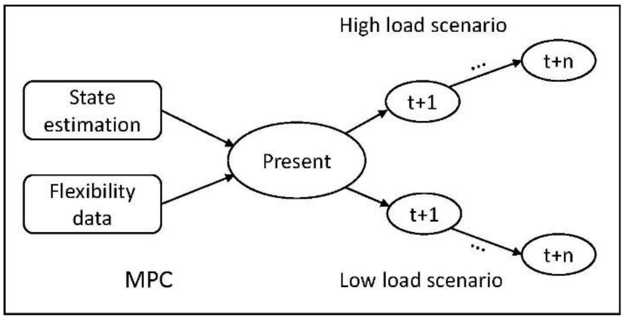

Figure 4 MPC optimization structure

If the flexibility sources are not fully activated when needed, it implies that at least some operational constraints are violated and penalization is applied. The tool uses double penalty method for every operational constraint: voltage magnitudes and line apparent power limits. The first penalty is soft, i.e., the penalty factor is low, but only limited violation quantity is allowed to be addressed with this penalty. There is a strong emphasis not to allow for high constraint violations so any violation quantity higher than allowed by the first penalty is penalized with much higher factor. Equations (6) and (7) implement double penalty approach for apparent power limits and voltage limits respectively. $\bar{S}$, $\underline{V}$ and $\bar{V}$ are apparent power and voltage limits and S^{pen1}, S^{pen2}, $\underline{V}^{pen1}$, $\underline{V}^{pen2}$, $\bar{V}^{pen1}$ and $\bar{V}^{pen2}$ are nonnegative penalty variables where versions with number 1 in the superscript are also bounded from the upper side to the desired value. The same penalized formulas are applied to both present and future time steps.

$$P^2 + Q^2 \leq (\bar{S} + S^{pen1} + S^{pen2})^2 \qquad (6)$$

$$\left(\underline{V} - \underline{V}^{pen1} - \underline{V}^{pen2}\right)^2 \leq (V^d)^2 + (V^q)^2 \leq (\bar{V} + \bar{V}^{pen1} + \bar{V}^{pen2})^2 \qquad (7)$$

Distribution system flexibility sources also provide services to TSO. We acknowledge that it is impossible to find global optimal solution for both TSO and DSO flexibility activation if the two optimizations are run separately. Theoretically, TSO can request flexibility activation that is in opposite direction that DSO needs. We resolve this issue by allowing the DSO to activate any quantity of opposite flexibility direction than TSO, as long as it has also activated the requested correct flexibility direction. This behaviour can be enforced using constraints (8) – (11) where left-hand-side variables, which are all nonnegative, are total distribution network up and down activated flexibility and right-hand-side are parameters, i.e. activation signals, as requested by the TSO.

$$P^{up\_DSO} \geq P^{up\_TSO} \qquad (8)$$
$$P^{dn\_DSO} \geq P^{dn\_TSO} \qquad (9)$$
$$Q^{up\_DSO} \geq Q^{up\_TSO} \qquad (10)$$
$$Q^{dn\_DSO} \geq Q^{dn\_TSO} \qquad (11)$$

The final key part of the optimization model is the objective function (12). It minimizes the flexibility activation costs $c^{flex\_activation}$ modelled as a convex square function as in formula (13) with a, b and c coefficients where $P^{up/dn}$ is any flexible device activation in any direction and constraint violation penalties from formula (14). Different coefficients are supported for every device, direction, penalty type and time step, i.e., present or future. For future time steps we generally consider lower penalty factors π^{pen1} and π^{pen2} since such unfavourable future scenarios are unlikely. $(S \mid \underline{V} \mid \bar{V})$ represents either apparent power or voltage up or down penalty variable. The objective function (9) sums activation costs and constraint violation penalties over all time periods t, devices, flexibility directions and constraints.

$$Min \sum_{t,dev,up/dn} c^{flex\_activation} + \sum_{t,constr.} c^{pen} \qquad (12)$$

$$c^{flex\_activation} = a \cdot \left(P^{up/dn}\right)^2 + b \cdot P^{up/dn} + c \qquad (13)$$

$$c^{pen} = \pi^{pen1} \cdot (S \mid \underline{V} \mid \bar{V})^{pen1} + \pi^{pen2} \cdot (S \mid \underline{V} \mid \bar{V})^{pen2} \qquad (14)$$

CONCLUSION

The ATTEST project provides among others a framework for TSO/DSO coordination and tools for DA AS procurement and RT activation in distribution grids. DA stage makes decisions based on flexibility bids and network data, while RT tool relies on state estimation and its decisions are driven by the AS procured schedules. Uncertainties are addressed in both tools with forecast scenarios. The tools aim to ensure secure distribution network operation and provide AS to TSO under unfavourable uncertainty realizations at minimal costs. The tools have been successfully tested on a variety of realistic models of distribution grids, both radial and weakly meshed, from UK, Croatia, Portugal and Spain. These datasets will be made publicly available during the course of the project.

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