# A Hybrid CMA-ES Approach for Distributed Grid Compliant Energy Scheduling

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Abstract-An ever growing share of renewable energy resources in the distribution grid imposes fluctuating and hardly predictable feed-in and thus demands new control strategies. On the other hand, combined with controllable, shiftable loads and battery capacity, these energy units set up new flexibility potentials for ICT-based control. So far, many approaches for harnessing this potential neglect the indispensable grid compliance of scheduling results due to the high computational complexity. We present a hybrid approach that enables distributed, agentbased algorithms for predictive energy planning to incorporate grid friendly behavior into agents' decision routines. We propose a scheme using a covariance matrix adaption evolution strategy (CMA-ES) for deciding on grid compliant solutions in a manyobjective approach. The integration with an agent-based greedy algorithm for decentralized predictive scheduling is demonstrated and the effectiveness of the approach is shown by several simulation experiments.

### I. INTRODUCTION

The future smart energy grid demands for new control paradigms that are able to incorporate a huge number of rather small, distributed and individually configured energy resources. In order to allow for a transition of the current central market and network structure to a decentralized smart grid, self-organization concepts are expected to become indispensable as an efficient management approach [1]. Small units will frequently pool together to coalitions for joint orchestration and better market potential. As the smart grid will have to delegate many control tasks to small and distributed energy resources (DER), control algorithms will have to cope with large problem sizes and with distributed and only locally available information.

Virtual power plants (VPP) are a well-known instrument for aggregating and controlling DER [2]. Concepts for several use cases (market-related as well as technical) have been developed. A frequent use case commonly emerging within VPP control is the need for scheduling the participating DER. Independently of the specific objective at hand, a schedule for each DER has to be found such that the schedule that finally is assigned is operable without violating any technical constraint. Ensuring the feasibility of a VPP scheduling solution is a crucial task [3], but has already been addressed by several approaches [3], [4], [5] at least with regard to being operable for the units.

Different from classical approaches, surprisingly low effort has so far been spent on integrating criteria for grid compliance or grid friendly behavior especially in distributed planning Sebastian Lehnhoff Department of Computing Science University of Oldenburg, Germany Email: sebastian.lehnhoff@uni-oldenburg.de

approaches, although due to the (electrically) distributed nature of the generators this is a fortiori necessary.

Without integration of grid constraints there is no guarantee that a solution that has been found by a self-organized group of distributed energy resources can be implemented when it comes to product delivery. Thus, at least objectives for a grid friendly plan should be integrated for a robust scheduling that minimize the need for control power or other grid management interventions. Without obeying higher-level requirements for stable grid operation, acceptance of new, decentralized algorithms within the smart grid will be hardly reached.

The rest of the paper is organized as follows. We start with an introduction to related approaches and a general outline of a distributed greedy approach that is going to be extended here. We continue with a description of the new decision approach that incorporates an evolution strategy for local decisions on suitable schedule assignments based on grid objectives. We evaluate the approach with several simulation studies and conclude with an outlook on future research directions.

# II. RELATED WORK

The problem of optimal power flow (OPF) is in general well-defined since the 1960s [6]. OPF is concerned with minimizing fuel cost of (classical) generators. Whereas the classical economic dispatch problem incorporates grid constraints merely as a single power balance constraint, OPF also is concerned with additional grid constraints like voltage and phasor angle bounds, e.g. [7]. Though, both approaches have the same objective of minimizing fuel (and thus operation) cost. Distribution of OPF has so far been scrutinized in terms of supporting different, competing grid operators in charge of different regions of the grid [6], [8] and/ or operate on specific grid topologies [9]. An extension to decentralized, negotiating agents on a per unit basis has so far not been comprehensively scrutinized.

Within the framework of today's (still mostly centralized) operation planning for power stations, different heuristics are already harnessed. Examples from the research sector are for instance shown in [10] or in [11]. This task of (short-term) scheduling of different generators is also known as unit commitment problem and assigns (in its classical interpretation) discrete-time-varying production levels to generators for a given planning horizon [12]. It is known to be an NP-hard problem [13] and determining an exact global optimum is not possible until ex post due to uncertainties and forecast errors.

Centralized approaches have long time dominated the discussion also for renewables' integration. [14], not least because a generator may achieve slightly greater benefit if optimization is done from a global, omniscient perspective [15]. The same holds true for OPF. Centralized methods are discussed in the context of static pools of DER with drawbacks and restrictions regarding scalability and particularly flexibility.

Recently, distributed approaches gained more and more importance. Different works proposed hierarchical and decentralized architectures based on multi-agent systems and market based computing [16], [17]. Newer approaches try to establish self-organization between actors within the grid [18], [19], [20]. Two examples for fully decentralized agent-based approaches are a greedy agent approach [21] and the combinatorial optimization heuristics for distributed agents (COHDA) [22].

An important aspect in smart grid control algorithms is constraint handling, as infeasible solutions that cannot be implemented afterwards by the energy units are worthless. Modeling constraints was rather simple for past easy controllable, large power plants. Versatile, small, individually embedded and operated energy generators and controllable consumers on the contrary have individual, often non-linear and complex constraints that restrict operations and define the flexibility that is offered to control algorithms for predictive planning. Some approaches have been developed to handle such individual constraints [3], [4]. In [21] and [23] a decoder approach based on support vector models has been integrated into agent-based approaches for predictive scheduling.

Although approaches for integrating many-objective optimization into smart grid planning procedures exist [22], [24], low effort has so far been spent on integrating grid compliance as constraint or grid friendly behavior as optimization objective into decentralized smart grid scheduling algorithms. On the other hand, for integrating electrical distance (as an indicator for the grid usage) [25] developed a metric that allows analysing grid related changes using graph theory. The metric can be used to compare different rescheduling options regarding grid usage for both dynamic clusters of distributed energy resources and for rescheduling static clusters like virtual power plants.

In the following, we propose a first integration scheme for grid objectives into the decision routine of agent-based predictive scheduling algorithms.

# III. A DISTRIBUTED GREEDY ALGORITHM FOR SCHEDULING

As opposed to the usual time series, we regard a schedule as real valued vector  $\boldsymbol{p} = (p_1, \ldots, p_d) \in \mathbb{R}^d$  with each element  $p_i$  denoting mean active power generated (positive values) or consumed (negative value) during the *i*-th of *d* time intervals. Starting time and width of each time interval are assumed to be known from context information. The feasibility of a schedule  $\boldsymbol{p}$  is defined by sets of unit specific technical and economic constraints.

One of the crucial challenges in operating a VPP arises from the complexity of the scheduling task due to the large amount of (small) energy units in the distribution grid [26]. In the following, we consider predictive scheduling, where the goal is to select exactly one schedule  $p_i$  for each energy unit  $U_i$  from a search space of feasible schedules with respect to a future planning horizon, such that a global objective function (e.g. resembling a target power profile) is optimized by the sum of individual contributions [27]. A basic formulation of the scheduling problem is given by

$$\delta\left(\sum_{i=1}^{m} \boldsymbol{p}_{i}, \boldsymbol{\zeta}\right) \to \min; \text{ s.t. } \boldsymbol{p}_{i} \in \mathcal{F}^{(U_{i})} \ \forall U_{i} \in \mathcal{U}.$$
(1)

In equation (1)  $\delta$  denotes an (in general) arbitrary distance measure for evaluating the difference between the aggregated schedule of the group and the desired target schedule  $\zeta$ . In order to compare results and for scalability reasons we used the mean absolute percentage error (MAPE)  $\delta(x, \zeta) = \frac{1}{d} \sum_{i=1}^{d} \left| \frac{\zeta_i - x_i}{\zeta_i} \right|$ .

To each energy unit  $U_i$  exactly one schedule  $p_i$  has to be assigned. The desired target schedule is given by  $\zeta$ .  $\mathcal{F}^{(U_i)}$  denotes the individual set of feasible schedules that are operable for unit  $U_i$  without violating any (technical) constraint. Solving this problem without unit independent constraint handling leads to specific implementations that are not suitable for handling changes in VPP composition or unit setup without having changes in the implementation of the scheduling algorithm [22].

Flexibility modelling can be understood as the task of modelling constraints for energy units. Apart from global VPP constraints, constraints often appear within single energy components; affecting the local decision making. Since these constraints are not of a distributed nature, they can be solved locally using central approaches. A widely used approach is the introduction of a penalty into the objective function that devalues a solution that violates some constraint [28]. In this way, the problem is transferred into an unconstrained one by treating fulfillment of constraints as additional objective. Another popular method treats constraints or aggregations of constraints as separate objectives, also leading to a transformation into a (unconstrained) many-objective problem [29].

For optimization approaches in smart grid scenarios, blackbox models capable of abstracting from the intrinsic model have proved useful [30], [31]. The original models do not need to be known at compile time. A powerful, yet flexible way of constraint-handling is the use of a decoder that gives a search algorithm hints on where to look for schedules satisfying local hard constraints (*feasible schedules*) [32], [31].

For our experiments, we used a decoder as described in [33]. Here, a decoder  $\gamma$  is given as mapping function

$$\gamma: \mathbb{R}^d \to \mathbb{R}^d; \ \gamma(\boldsymbol{p}) \mapsto \boldsymbol{p}^*.$$
(2)

With  $p^*$  having the following properties:

- $p^*$  is operable by the respective energy unit without violating any constraint,
- the distance ||p − p<sup>\*</sup>|| is small; where the term small depends on the problem at hand and often denotes the smallest distance of p to the feasible region.

With such decoder concept for constraint handling one can now reformulate the optimization problem as

$$\delta\left(\sum_{i=1}^{m} \gamma_i(\boldsymbol{p}_i), \boldsymbol{\zeta}\right) \to \min, \tag{3}$$

where  $\gamma_i$  is the decoder function of unit *i* that produces feasible, schedules from  $p \in [0, p_{max}]^d$  resulting in schedules that are operable by that unit. Please note, that this is a constraint free formulation. With this problem formulation, many standard algorithms for optimization can be easily adapted as there are no constraints (apart from a simple box constraint  $p \in [0, p_{max}]^d$ ) to be handled and no domain specific implementation (regarding the energy units and their operation schedules) has to be integrated. Equation (3) is used as a surrogate objective to find the solution to the constrained optimization problem equation (1).

With these preliminaries, in [21] a distributed agent-based greedy approach has been proposed for solving the scheduling problem Eq. (3). This section briefly introduces the distributed approach which is then extended to incorporating grid compliance.

One type of agent is assumed: the control agent  $A_i$  of a single energy resource  $U_i$  with the following responsibilities/ capabilities:

- Simulating the underlying physical device in order to determine operable example schedules for training the decoder.
- Determining the schedule for one's own physical device that minimizes the overall loss.

The procedure for optimizing the aggregated schedule is the one depicted in Fig. 1.

```
\mathcal{A} \leftarrow \text{List of all agents}
if is initiator then
    p_{\Sigma} \leftarrow zeros(d)
else
   p_{\Sigma} \leftarrow aggregated schedule
   //decide on own contribution
   oldsymbol{p}_{o} \leftarrow oldsymbol{p}_{\Sigma} - oldsymbol{p}_{A} //schedule of all other agents
   \boldsymbol{p}_A \leftarrow \gamma(\boldsymbol{\zeta} - \boldsymbol{p}_o)
   p_{\Sigma} \leftarrow p_{\Sigma} - p_o + p_A
   if no stop criterion met then
        choose random agent A \in \mathcal{A}
        send message with p_{\Sigma} to A
    else
        publish solution p_{\Sigma}
    end if
end if
```

Fig. 1. Greedy algorithm that each agent repeatedly executes for successive solution improvement starting from a zero solution  $p_{\Sigma}$  denoting the aggregated overall solution and  $p_A$  denoting the individual current contribution of the agent [21].

Within a group of agents A, one agent is randomly chosen to start the procedure. In the greedy approach, each agent is in charge of controlling one DER and participates in the distributed procedure of determining schedules for each DER such that the aggregated schedule best fits a given objective schedule. An initiator initializes the solution with all values to zero. Then, solution improvement begins. An agent adds up all schedules (known from a received message) from all other agents. This is equivalent to subtracting one's own schedule from the aggregated solution. In a next step, the difference vector  $\Delta p = \zeta - (p_{\Sigma} - p_A)$  of this sum to the desired target schedule is determined. This difference represents the optimal schedule for the current agent in the following sense: if this schedule could be delivered by the respective DER without violating technical constraints, the target could be reached exactly. Therefore, the agent now determines the nearest schedule to  $\Delta p$  that is actually operable by the device. This nearest schedule can be easily calculated with the help of the mapping  $\gamma$  that has been described in the previous section. Function  $\gamma$  maps an arbitrary schedule (in our case difference schedule  $\Delta p$ ) into the region of feasible schedules and delivers the respective operable schedule that is nearest to  $\Delta p$ , because it uses the shortest trace to the feasible region.

In this way, each DER agent chooses a schedule that is a compromise of being feasible (automatically ensured by mapping  $\gamma$ ) and doing one's own best in bringing forth the overall solution towards the wanted adaption to the target schedule as much as possible each time when it is the respective agents turn. By one after another, the overall solution (the aggregated schedule) is successively improved. Applicability to asynchronous update has been shown in [21]. If the objective is to adapt to a given target schedule, the only information that has to be passed around (or made globally available) is the aggregated overall solution (as sum of all local solutions) and the desired target schedule. This is sufficient as each agent may remember his own local schedule that has been determined previously. All other information can be determined by local information.

So far, neglecting grid requirements is the major drawback of this approach. The same holds true for many other algorithms even in many-objective cases, e. g. [34], due to the high computational complexity of this objective. Evaluating grid compliance as objective encompasses solving complex load flow computations in every evaluation of a schedule choice during the main scheduling task.

# IV. CMA-ES FOR DECIDING ON GRID OPTIMAL SCHEDULES

In the field, power quality comprises a wide range of criteria and effects starting from high-frequent, transient effects [35]. We will focus here on steady state criteria using the example of voltage band restrictions and maximum current. Although our approach is not restricted to a specific timely resolution, our simulations are conducted in 15-minute time slots with averaged power as usual in contemporary energy markets.

In steady state, power flow analysis is used for calculating nodal voltage and currents based on nodal power (demand and/ or feed-in). When the grid is operating in steady state, power flow analysis gives insight into power flow under specified conditions described by a set of non-linear equations [36]. Usually, iterative methods are used for solving the system of equations. Given are active and reactive power for each node



Fig. 2. Example result for a scenario with 50 chp and 96-dimensional schedules. The top chart shows target and aggregated (optimization result) schedule. The second chart emphasizes the residual error (absolute deviation to the target). The lower charts show the individual schedules and the resulting temperatures in the thermal buffer store. Allowed ranges defined by several constraints are highlighted by the grey area.

loop

wait for message if message then  $P_A \leftarrow p_{A_{i_n}}$ , denoting the so far selected schedules of all agents  $A \in \mathcal{A}$  $p_o \leftarrow \sum P_A - p_A$ initialize CMA-ES while no stopping criterion met do generate new solution population S after CMA-ES sampling for all  $\boldsymbol{x} \in \boldsymbol{S}$  do calculate genotype  $\boldsymbol{p}_x \leftarrow \gamma(\boldsymbol{x})$ determine error  $\delta_{\boldsymbol{p}} = \delta(\boldsymbol{p}_o + \boldsymbol{x}, \boldsymbol{\zeta})$  $\boldsymbol{P}'_{\mathcal{A}} \leftarrow \boldsymbol{P}_{\mathcal{A}}; \, \boldsymbol{P}'_{\mathcal{A}}[i] \leftarrow \boldsymbol{x}$ calculate grid objective  $\delta_G = g(G, \mathbf{P}'_{\mathcal{A}})$  with Newton-Raphson evaluate solution candidate x by weighting error  $\delta_p$  and objective  $\delta_G$ end for update covariance matrix and step sizes according to CMA-ES approach end while send best found solution to neighboring agents end if end loop

Fig. 3. Improved decentralized greedy with grid objectives for decision.

in the grid. The goal is to obtain angle and magnitude of the voltage for each node. Based on the voltage information, power flow can be determined in a subsequent step. The Newton-Raphson approach [37], [38] starts with an educated guess for the unknown voltage parameters and by constructing the following system of linear equations:

$$\begin{pmatrix} \Delta \theta \\ \Delta |V| \end{pmatrix} = -\boldsymbol{J}^{-1} \begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix}, \tag{4}$$

Where  $\Delta P$  and  $\Delta Q$  are given by Taylor series with N terms

$$\Delta P_{i} = -P_{i} + \sum_{k=1}^{N} |V_{i}| \cdot |V_{k}| \cdot (\Re \bar{Y}_{ik} \cos \theta_{ik} + \Im \bar{Y}_{ik} \sin \theta_{ik})$$
  
$$\Delta Q_{i} = -Q_{i} + \sum_{k=1}^{N} |V_{i}| \cdot |V_{k}| \cdot (\Re \bar{Y}_{ik} \sin \theta_{ik} - \Im \bar{Y}_{ik} \cos \theta_{ik})$$
  
(5)

With  $\Re \overline{Y}_{ik}$  and  $\Im \overline{Y}_{ik}$  denoting real and imaginary part of the respective entry in the nodal admittance matrix  $\overline{Y}$ . The Jacobian J is used to iterate the solution towards the root with the Newton-Raphson iteration scheme [36]. For solving the load flow problem, several solvers are readily available [39], [38], [40], [41], [42].

Let the grid be defined by G = (N, L) with the set of nodes N and a set of lines  $L = (\ell, R, X, C)$  with length  $\ell$ , resistance R, reactance X and capacity C. Each node  $N_i$  is characterized by the power drawn from or fed into the grid at node  $N_i$ . We extend the mere check for grid compliance to optimizing grid friendly behavior of the group of units. As this is a rather vague requirement, we introduce an additional objective  $\delta_G = g(G, P_A)$  that is to be minimized alongside with objective Eq. (3).  $P_A$  is a matrix with each row corresponding to the schedule of one agent, thus defining feedin for each node for each time interval. Objective q may reflect the number (and height) of grid compliance violations. For our experiments we have chosen to minimize deviations from the voltage band and minimize current flow on specific lines. In general, other definitions of g can be easily exchanged within the agent-based approach. In this work we focus on issues of technical integration into the distributed algorithm.

Thus, we extend the decision procedure of an agent from mere determining a nearby feasible schedule next to the theoretical optimal one (cf. Fig. 1) to an internal optimization problem. Let  $x \in \mathbb{R}^d$  be an arbitrary schedule as an internal representation (genotype); x does not obey any constraint. Then the new schedule selection of an agent is determined by

$$p_A \leftarrow \arg\min d(\boldsymbol{x}) = w \cdot \delta(\boldsymbol{p}_o + \gamma(\boldsymbol{x}), \boldsymbol{\zeta}) + (1 - w) \cdot g(G, \boldsymbol{P}_A)$$
(6)
Here, parameter  $w \in [0, 1]$  denotes a weighting of both



Fig. 4. Sensitively to the weight w for balancing power balance and grid criteria. On the left: relative error (residual error relative the case of zero weight with completely disregarding the respective criterion) for different weightings when integrating weight merely into objectiv function; in the middle: relative residual error of each criterion for extended decision functions; on the right: the case of minimizing current flow.

objectives. The first term denotes resemblance of the given aggregated schedule (sum of the aggregation of all others' schedules and a candidate schedule x chosen form the respective flexibility by  $\gamma$ ) to the desired target schedule  $\zeta$ . The second term incorporates a grid objective (e.g. voltage band violation or max. current exceed) described by function g. Both are to be minimized with different emphasis described by weighting w.

Optimization problem Eq. (6) has to be solved for every objective decision procedure. Due to the non-linear character of g, a heuristics is most suitable for solving. As the formulation contains no constraint due to the usage of a decoder function  $\gamma$ , in general any evolutionary algorithm may be used. We decided to use the covariance matrix adaption evolution strategy [43], [44] (CMA-ES), because of its proved efficiency. CMA-ES as strategy for solving the decision problem is known to perform well while using only a small number of objective evaluations [45], [46].

CMA-ES aims at learning lessons from previous successful evolution steps for future search directions. A new population is sampled from a multi variate normal distribution  $\mathcal{N}(0, \mathbf{C})$ with covariance matrix C which is adapted in a way that maximizes the occurrence of improving steps according to previously seen distributions for good steps. Sampling is weighted by a selection of solutions of the parent generation. In a way, the method learns a second order model of the objective function and exploits it for structure information and for reducing calls of objective evaluations. An a priori parametrization with structure knowledge of the problem by the user is not necessary as the method is capable of adapting unsupervised. A good introduction can for example be found in [47]. Especially for non-linear, non-convex black-box problems, the approach has shown excellent performance [47]. CMA-ES is initially not designed for integrated constraint handling in constrained optimization. Nevertheless, some approaches for integrating constraint handling have been developed. In [48] a CMA-ES is introduced that learns constraint function models and rotates mutation distributions accordingly. In [49] an approximation of the directions of the local normal vectors of the constraint boundaries is built by accumulating steps that violate the respective constraints. Then, the variances of these directions are reduced for mutation.

Unfortunately, these approaches are not applicable for integration into agent-based decisions as the optimization model has to be built on the fly and fully automatically according to information that is received by the agent. Thus, we employed the decoder technique.

In the original implementation, the greedy agent algorithm decides on the best possible schedule for its own energy unit by using a decoder and thus delegating the internal optimization (finding the best from the own set of flexibility) to a single decoder function call. The same holds true e.g. for COHDA. Searching the best feasible schedule from own flexibilities including grid objectives, on the other hand, involve solving a complete optimization problem. In this way, in each call of the decision routine of an agent, and thus for each evaluation of the objective function of the predictive scheduling (3) an internal optimization problem has to be solved; making evaluation rather slow. For this reason, an optimization approach is needed that draws performance from substituting objective function calls from quicker surrogate models. Fig. 3 shows the general process for a single agent participating in the extended approach using CMA-ES for local decisions.

#### V. SIMULATION RESULTS

## A. Setup

As a model for distributed energy resources we used a model for co-generation plants that has already served in several studies and projects for evaluation [3], [33], [50], [23], [51]. This model comprises a micro CHP with 4.7 kW of rated electrical power (12.6 kW thermal power) bundled with a thermal buffer store. Constraints restrict power band, buffer charging, gradients, min. on and off times, and satisfaction of thermal demand. Thermal demand is determined by simulating a detached house (including hot water drawing) according to given weather profiles. For each agent the model is individually (randomly) configured with state of charge, weather condition, temperature range, allowed operation gradients, and similar. From these model instances, the respective training sets for building the decoders have been generated with the sampling approach from [52].

All algorithms have an individual, strategy specific set of parameters that usually can be tweaked to some degree for a problem specific adaption. Nevertheless, default values that are applicable for a wide range of problems are usually available. For our experiments, we used the following default settings for the CMA-ES. The (external) strategy parameters are  $\lambda, \mu, w_{i=1...\mu}$ , controlling selection and recombination;  $c_{\sigma}$  and  $d_{\sigma}$  for step size control and  $c_c$  and  $\mu_{cov}$  controlling the covariance matrix adaption. We have chosen to set these values after [47]:

$$\lambda = 4 + \lfloor 3\ln n \rfloor, \quad \mu = \left\lfloor \frac{\lambda}{2} \right\rfloor, \tag{7}$$

$$\boldsymbol{w}_{i} = \frac{\ln(\frac{\lambda}{2} + 0.5) - \ln i}{\sum_{\mu}^{j=1} \frac{\lambda}{2} + 0.5) - \ln i}, \ i = 1, \dots, \mu$$
(8)

$$C_c = \frac{4}{n+4}, \ \mu_{\rm cov} = \mu_{eff},$$
 (9)

$$C_{\rm cov} = \frac{1}{\mu_{\rm cov}} \frac{2}{(n+\sqrt{2})^2} + \left(1 - \frac{1}{\mu_{\rm cov}}\right) \min\left(1, \frac{2\mu_{\rm cov} - 1}{(n+2)^2 + \mu_{\rm cov}}\right).$$
(10)

These settings are specific to the dimension N (in our case: schedule dimension d) of the objective function. An in-depth discussion of these parameters is also given in [53].

As grid topology, so far we considered all CHP being on a single line (each CHP as a node, one as slack node) and scrutinized the voltages at every node as well as the current flows in each connecting line (specified as  $\emptyset$ 120 mm<sup>2</sup>, R=0.253  $\Omega$ /km, X=0.0804  $\Omega$ /km,  $I_{max}$ =240 A). Consumption at each node was generated randomly at the level of rated power of the CHPs and kept constant for each experiment run. Variable feed-in is given by the CHP.

#### B. Results



Fig. 5. Convergence behavior of different problem sizes and 16- 5(a) and 96-dimensional 5(b) schedules. One iteration denotes the execution of one agents' decision procedure.

With our simulations we first tested the effect of replacing the decision making part of an agent with an optimization approach. As grid objective we w.l.o.g minimized the deviation from rated voltage at node 4. Figure 4 shows the remaining error for each objective after optimization depending on the value of weight w (relative to the worst result). Figure 4(a) shows the result for integrating the new objective function (6) merely as objective in the original agent-based approach from [21]. Figure 4(b) shows the same experiment with the new decision procedure based on an integrated CMA-ES as decision procedure. As can be seen, the effect on the (dominant) main objective of resembling the target schedule does not degrade. Note, a weight of w = 0 denotes a complete neglecting of the main objective; w = 1 optimizes only the main objective. Figure 4(b) shows a way better improvement for the grid objective for the new decision routine (up to a residual error of 85% instead of mere 98% as in Fig. 4(a)). Figure 4(c) shows the result for minimizing the current flow on line 3.

Looking at convergence behavior, the algorithm with improved decision procedure converges almost as quick as had been reported for the original algorithm [21] in terms of iterations. Figure 5(a) shows some results for different problem sizes (number of units) and 16-dimensional schedules. The term iteration in these simulations refers to the number of decision procedures that are executed by the agents. Specifically for this simulation the agents are executed synchronously to enable solution quality measurement after each decision. The algorithm converges quick because the decoder takes over a share of the optimization work by delivering good solutions directly without a need for unsupervised search. Regarding achievement of the main objective (resembling the wanted target schedule), the same seems to hold true for the improved version here when counting iterations. Figure 5(b) shows a second example with 96-dimensional schedules. The dimensionality of the schedules has a minor effect because the decoder delivers improvements for every dimension in the schedule at once. Thus, the performance of our proposed integration of grid objectives depends mainly on the performance of executing the sub-optimization process inside the decision procedure.

Several factors have an impact on the performance of the CMA-ES optimization process inside the decision procedure. Thus, Table I lists several results of simulation runs with different parametrizations. Depicted are means and standard deviations of 25 simulation runs each. Each run was initialized with randomly generated CHP-models (uniform distributed buffer and outdoor temperatures). For the thermal demand, two classes of CHP have been used: one with randomly generated thermal demand for each time period and one class with a thermal demand following standard profiles. Load at each node has been randomly generated normal distributed with rated generation as expectation and 1 kW as variance once for each experiment and was then kept constant for all simulation runs.

The simulations have been conducted for several combinations of number of CHP n, dimensions of schedules d, weighting w, and a threshold  $\epsilon$  as an additional stopping criterion for the CMA-ES. Successive improvements below  $\epsilon$ (stall of the algorithm) lead to an abort and the result was considered good enough.

Table II show an additional experiment with all parameters kept constant (n = 5, d = 16, w = 0.2) except for  $\epsilon$  showing the huge potential for saving CMA-ES objective function evaluations and thus Newton-Raphson load flow calculations without significantly decreasing the quality of the final solution. The situation does not shift before  $\epsilon = 0.1$ . Nevertheless, several thousand power flow calculations are still challenging. Thus, future work should try to replace the Newton-Raphson calculations with probabilistic, estimating approaches.

# VI. CONCLUSION

Power flow optimization had long since been integrated into classical economic dispatch algorithms for traditional unit commitment. On the other hand, changes in the grid by a steadily growing pervasion with renewable energy and a

TABLE I. COMPARISON OF OBJECTIVE EVALUATIONS FOR DIFFERENT SETTINGS OF NUMBER OF CHP n, schedule dimension d, weight w and quality threshold  $\epsilon$ . The number of evaluations denotes the absolute number of grid objective evaluations (note that for each dimension a Newton-Raphson power flow calculation has to be conducted). Additionally the number decision procedure calls and the relative number of grid objective calculations per decision procedure call and the achieved quality (weighted sum of both percentage errors) are denoted.

#	n	d	w	$\epsilon$	decisions	evaluations	rel. evaluations	quality
1	5	16	0.2	0.0001	$19.00 \pm 8.10$	18038.90 ± 8337.95	942.16 ± 117.98	$0.130\pm0.029$
2	10	8	0.2	0.0001	$70.00 \pm 24.94$	$38059.00\pm15372.17$	$534.97\pm52.48$	$0.255\pm0.013$
3	10	16	0.1	0.001	$57.00 \pm 025.84$	$32800.20\pm15322.69$	$572.23\pm18.35$	$0.258\pm0.016$
4	10	16	0.0	0.001	$28.00 \pm 9.19$	$16108.00\pm5166.99$	$576.69\pm12.13$	$0.264\pm0.013$
5	10	16	0.8	0.001	$51.00 \pm 21.83$	$31433.40\pm14212.23$	$609.40\pm30.99$	$0.228\pm0.031$
6	10	16	1.0	0.001	$58.00 \pm 23.47$	$36713.20\pm14576.02$	$634.18\pm45.50$	$0.259\pm0.076$
7	10	16	0.1	0.01	$47.00 \pm 23.11$	$20628.20\pm10377.83$	$437.33\pm25.92$	$0.271\pm0.021$
8	25	8	0.2	0.01	$165.00 \pm 47.43$	$26757.00\pm7811.15$	$162.08\pm6.23$	$1.817\pm0.045$
9	25	16	0.2	0.001	$157.50 \pm 44.17$	$37610.50\pm10639.03$	$238.49 \pm 5.36$	$1.756\pm0.043$

TABLE II.Sensitivity analysis regarding the stallthreshold  $\epsilon$  that stops the CMA-ES early as soon as successive<br/>error improvement falls below $\epsilon$ .

$\epsilon$	decisions	evaluations	rel. evaluations	quality	
0.0	$23.50 \pm 5.30$	$116762.50\pm 26515.08$	4966.57 ± 33.70	$0.118 \pm 0.022$	
0.0001	$28.50 \pm 16.67$	$18152.50 \pm 11148.78$	$637.88\pm85.69$	$0.138\pm0.022$	
0.001	$23.50 \pm 11.56$	$7925.00 \pm 4311.09$	$333.56 \pm 37.58$	$0.133\pm0.027$	
0.01	$20.00 \pm 7.07$	$3935.00\pm1284.08$	$198.36\pm16.51$	$0.167 \pm 0.036$	
0.1	$16.50 \pm 9.14$	$234.50\pm137.42$	$14.01\pm1.64$	$409.186\pm23.044$	

shift away from a strict 'load follows consumption' paradigm already started research on new control strategies. Due to the strongly growing problem sizes, induced by the large number of generators (bundled with small controllable consumers), decentralized, self-organized approaches seem to be the most promising technology to cope with scalability issues. So far, grid objectives had scarcely been considered or integrated into these new control strategies.

We developed an approach that for the first time integrates grid objectives by optimizing grid friendly behavior into decoder-based decentralized load planning.

Developing specific criteria for evaluating grid compliance or rather grid friendly behavior has so far not been in the scope of this work. Here, future research will still have to be conducted. We presented a framework for integrating such criteria into distributed scheduling procedures with the hybrid approach of integrating CMA-ES many-objective optimization into an agent's decision routine and thus enabled an easy integration of such grid criteria.

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