

## AN ONLINE LEARNING ALGORITHM APPROACH FOR LOW VOLTAGE GRID MANAGEMENT

Philipp GOERGENS

RWTH Aachen University – Germany  
goergens@ifht.rwth-aachen.de

Fabian POTRATZ

RWTH Aachen University – Germany  
potratz@ifht.rwth-aachen.de

Claas MATROSE

RWTH Aachen University - Germany  
matrose@ifht.rwth-aachen.de

Sven SCHUMANN

RWTH Aachen University – Germany  
schumann@ifht.rwth-aachen.de

Univ.-Prof. Dr. -Ing. Armin SCHNETTLER

RWTH Aachen University – Germany  
schnettlar@ifht.rwth-aachen.de

Stefan WILLING

RWE Deutschland AG – Germany  
stefan.willing@rwe.com

Dr.-Ing. Thomas SMOLKA

Maschinenfabrik Reinhausen- Germany  
t.smolka@reinhausen.com

### ABSTRACT

*The smart grid concept introduces improved possibilities for coordinated distribution grid management in order to increase the receptivity for Renewable Energy Sources while simultaneously guaranteeing a safe and reliable grid operation. This paper presents a smart grid control strategy for real-time low voltage (LV) grid management applications based on an online-learning algorithm. It enables for the derivation of a schedule-forecast for installed assets. Next to coordinated voltage and line utilization control the approach optimally exploits the potential benefits of innovative grid assets for grid operation. The performance of the algorithm is demonstrated by a simulation study using a typical LV grid.*

### INTRODUCTION

A constantly growing penetration of decentralized generation in distribution grids is causing a massive need for upgrading of low and medium voltage grids in Germany [1]-[2]. Consequently, innovative approaches have to be exploited in order to reduce the cost for grid reinforcement as much as possible. Flexible customers / demand side management and innovative grid assets such as MV/LV transformers with on load tap changers (OLTC) offers such possibilities.

The “Smart Operator” project<sup>1</sup> aims at proving the feasibility of a centralized control approach to optimize the operation of low voltage grids. Simulation studies, laboratory testing and three field trials will be conducted in order to gain experience with the required primary equipment, information and communication technology (ICT) as well as mathematical optimization methods [3]. This paper presents a new online-learning optimization

algorithm, which will be applied within the Smart Operator project.

### MANAGEMENT ALGORITHMS FOR DISTRIBUTION GRIDS

Management algorithms and operation principles for smart distribution grids can be classified into centralized controls with ICT and decentralized grid management approaches. Examples for decentralized methods are controls like Q(U)-control in PV-inverters.

Centralized control paradigms make use of a large variety of active grid components – innovative grid assets as well as controllable generators, storage systems and demand side management (DSM). By means of ICT, well-defined coordination of all controllable assets and the use of forecasting-methods a nearly optimal grid operation can be reached [3]. However, required control algorithms have to be capable of handling the enormous complexity of such systems in order find the optimal solution for grid operation.

#### Complexity and requirements of control strategies

The complexity in the optimal operation of a low voltage grid on the one hand comes from the large number of assets and therefore from possibilities to respond to a certain problem. In a LV distribution grid equipped with multiple storage systems, OLTC transformers and DSM in every household, there are millions of possible (but not necessary reasonable) states in which the grid can be operated (named “system options” in this paper).

Furthermore, such algorithms have to deal with highly stochastic behavior of load and generation within the grid. Storage-units increase the complexity by imposing the need to forecast the grid state for a certain period of time.

With the focus on low voltage distribution grids the algorithm to be developed must be able to operate the wide range of LV distribution grids without the need for intensive adaptations. Urban areas with a high load density have to be controllable as well as rural areas with low load density and long feeders.

<sup>1</sup>of RWE Deutschland AG, PSI AG, PSI Nentec GmbH, Horlemann Elektrobau GmbH, Hoppecke GmbH & Co. KG, Maschinenfabrik Reinhausen GmbH and Stibel Eltron GmbH & Co. KG

Due to the large number of grids and rather small installation space in a MV/LV station embedded systems with rather low computational power compared to a desktop computer has to be used.

## ONLINE LEARNING ALGORITHMS

The aim within the “Smart Operator” project is to achieve optimal grid operation by the means of minimizing to voltage deviation and line utilization at all time. Thus, a mixed-integer, stochastic, non-linear and combinatorial programming problem arises. To face this problem different optimization methods are – in principle – suitable. Approaches like mixed-integer linear programming have a lack in computational time since the effort increases exponentially with the number of solutions. Therefore, those methods will be neglected. Heuristical methods like genetic algorithms cannot guarantee the globally optimal solution. A suitable alternative for a grid management are numeric-iterative methods. The idea is to repeat the same computation step several times by using the solution of the former steps to converge to the optimum. One form of these kinds of algorithms is the randomized weighted majority (RWM) algorithm, which is discussed in detail in the following.

### Randomized Weighted Majority Algorithm

The randomized weighted majority algorithm is recommended for repetitive decision problems with incomplete information and high number of possible solutions [4]. Its strength has been shown for different use cases in game theory [5]. One of these use cases is well adaptable to the present problem as it can cope with incomplete information. Its name is partial information game or Bandit Setting. Similar to the fortune slot machine and their according probabilities in [5], the approach presented in this paper distinguishes between different system options. All system options have a different probability to be chosen as described before. The basic idea of the algorithm consists of six steps that build an iterative loop (see Fig. 1).

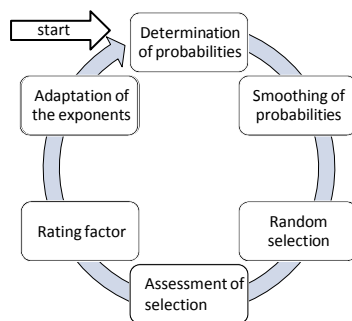


Figure 1: Schematic representation of the RWM

The goal is to find good solutions which are evaluated very iteration by the use of an objective function. With the help

of the assessment for every actual solution a probability can be derived and expresses the quality with respect to a certain objective function. A full description of this methodology can be found in [5].

## ADAPTATION OF THE BASIC ALGORITHM

In this section the algorithm in its basic form is adapted to match the given grid optimization problem as well as the restricted hardware capabilities. Therefore, the objective function is explained in detail and further simplification steps are shown. The development of the grid management and forecast algorithm is presented as well.

### Objective Function

Within the Smart Operator project, the aim is to keep the voltage and line utilization in predefined bands. Therefore, an objective function has to be formulated that can handle real-time data of voltage and current as input. DIN EN 50160 [6] can be taken as assessment base. In order to fulfill the voltage requirements, the penalty term  $\Delta U$  describing the voltage deviation from the nominal voltage is calculated for every bus. Afterwards, all the penalty terms of all  $M$  buses are summed as shown in Formula (1):

$$\Delta U_i = \left(1 - \frac{U_i}{U_N}\right)^2 \text{ if } U_N - U_B < U_i < U_N + U_B \quad (1)$$

$$\Delta U_i = \left(\frac{U_i}{U_N}\right)^G \text{ if } U_i \geq U_N + U_B$$

$$\Delta U_i = \left(1 + 1 - \frac{U_i}{U_N}\right)^G \text{ if } U_i \leq U_N - U_B$$

$$\Delta U(t) = \sum_{i=1}^M \Delta U_i$$

where  $\Delta U_i$  weighted voltage deviation in p.u. of  $i^{\text{th}}$  bus  
 $U_i$  actual voltage  
 $U_N$  nominal voltage  
 $U_B$  band voltage (to be predefined)  
 $G$  weighting factor

The weighting factor  $G$  has to be greater than two in order to increase the penalty for non-compliance of the voltage band.

To minimize the line utilization a mathematical expression is formulated so that utilization beneath the limit of the long term rating punishes only very low, but increases the penalty for high utilization and clearly detects injuries as demanded within the Smart Operator Project. Therefore, Formula (2) shows the penalty function for the line utilization term.

$$\Delta S(t) = \sum_{i=1}^L \left( \frac{\sqrt{P_i(t)^2 + Q_i(t)^2}}{S_{\text{Limit}}} \right)^G \quad (2)$$

where  $\Delta S$  weighted total apparent power of lines in p.u.  
 $P_i$  active power of line  $i$   
 $Q_i$  reactive power of line  $i$   
 $S_{\text{Limit}}$  apparent power limit  
 $G$  weighting factor

The determined apparent power  $\Delta S$  of every line  $i$  are summed over the number of all line  $L$  as well. The

weighting factor  $G$  can be used here similar to Formula (1). Altogether, the final objective function can be formulated as followed:

$$x_{it}(t) = e^{-\frac{X \cdot \Delta U(t) + Y \cdot \Delta S(t)}{\ln(x_{Max} + 1)}} \quad (3)$$

$$x_{Max} = \text{Max} [X \cdot \Delta U(t) + Y \cdot \Delta S(t) \forall t \in (0, t)]$$

*with*  $X + Y = 1$

where  $X$  voltage deviation weighting factor  
 $Y$  line utilization weighting factor  
 $x_{it}$  objective function  
 $x_{Max}$  highest hitherto penalty

Formula (3) of the objective function transforms the formerly presented penalty terms into a remuneration term since a better convergence can be reached. This can be achieved by using the hitherto maximal penalty expression as quotient.

### Learning Process Adaptation

The households and distributed generation unit patterns in a distribution grid differ with respect to short- and long term consumption over time. E.g. PV-units reach a higher generation peak around noon than at night and also the maximum height differs from summer to winter months. A classical learning algorithm is not able to cope with these seasonal changes, as it tries to learn that kind of behavior without any adaptations.

Therefore, strategies are introduced which divide the pre-learning process. Each strategy is trained individually for a certain grid state and later linked to a set of external information (temperature, solar radiation, weekday and time). The algorithm learns which strategy is effective at which external information running basically the same algorithm as described above. The strategies itself are determined by a pre-learning-phase. The whole algorithm learns when to use a certain strategy and is able to adopt each strategy over time as the supply task changes.

### Simplifications on the algorithm

There are a number of simplifications of the algorithms in order to enable an implementation into restricted hardware within the field trial (see [3]). Simplifications can reduce the number of possible grid states and will be presented in the following.

The algorithm divides the grid into separate LV feeders. The individual evaluation of the state of each feeder enables the algorithm to react to a critical state by switching the assets of the respective feeder, only. Additionally, only the best states of all feeders are combined and are considered as system options. These numbers can be adjusted regarding the size of the operated distribution grid. The possibility of eliminating a rather good state rises with limiting the number of possibilities; therefore this parameter must be adjusted carefully.

Depending on the number of households using DSM the feeder can be separated into several parts. Households located geographically close to each other and using DSM

are clustered into one feeder-part. Consequently, they are treated as one big household. In real-time control they are individually addressed again by disaggregation. Thus, the number of possible grid states is reduced, assuring at the same time an equal treatment of each DSM household in the grid.

### Grid management and forecast

An intensive learning process assures the probability vectors to be well trained and therefore the vectors are converged to the best system option. Using the different strategies an asset schedule forecast for certain situations is derived by picking the according best system option. Based on the information learned and the according forecast a grid management algorithm is implemented.

Similar to the learning process of the RWM a load flow calculation serves as assessment application. Measured data together with the knowledge about the actual settings of all assets allows calculating the grids state.

Consequently, after this assessment, all controllable assets are set according to the forecast and an assessment is conducted similarly. The setting which fulfills the objective function best is picked in order to get a better state. To minimize switching actions the actual state assessment is weighted with a factor of 1.1 since this factor leads to a stable grid management determined in a pre-analysis.

Nevertheless, if the objective function is injured, an unscheduled control is done based on the probability vectors which can cover the whole grid or only parts of it. However, if no solution can be found a backup control based on an expert system<sup>2</sup> is conducted.

### CASE STUDY

The developed algorithm is tested on a typical 153-node LV grid with four feeders and a 250 kVA transformer. A typical summer day with probabilistic loads and PV generation is regarded. The resolution is set to 1 h but can freely be adjusted. Table 1 summarizes all assets that can be controlled by the algorithm with the according states that build the system options. The battery is discretized to its 4-quadrant operating area. A reasonable power dimension of the battery for the present grid is determined to be +/- 3 kW / 3 kVAr in a pre-analysis.

<i>Asset</i>	<i>States</i>	<i>Attributes</i>
OLTC	9	4 % per state
Switch	2	on / off
Battery	9	+/- 3 kW / kVAr

**Table 1: Considered assets within the simulation**

Also considering households with DSM aggregated to one big household per feeder with three different load profiles, a

<sup>2</sup>A more elaborate analysis is due to be published by the authors.

total of 10,368 system options are generally possible. The algorithm detected 756 as appropriate from the grid's point of view. Therefore, the others are neglected for the grid management.

To cover every possible grid state for real-time grid management, a systematical learning phase is conducted. This leads to 216 strategies that cover every load combination of the four feeders that are built up on their power limits derived out of historical data.

For the simulation of grid operation the households with DSM are modeled as consumers which can randomly exhibit three different load profiles and thus cannot be changed. Only if the algorithm has to unexpectedly intervene the profiles can be altered.

## Results

Trying to fulfill the objective function to its best figure 2 is depicting the average voltage deviation with and without control.

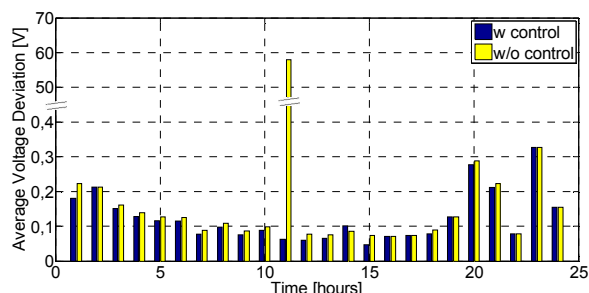


Figure 2: Average voltage deviation in operating period

At first glance, hour 14 shows that the voltage deviation with control seems to be worse compared to no switching application. Since the objective function also considers formula (2), the algorithm assessed a less utilized line to be more suitable than an increased voltage at some buses. In order to demonstrate the algorithm's behavior in unforeseen situations a voltage drop to 0.85 p. u. at MV level has been simulated in hour 11. Without switching the voltage band would be violated as to see in figure 2 at hour 11. Thus, the algorithm intervenes and uses the tap changer. Figure 3 shows the asset schedule within the operating period. The switch is not depicted since it has never been used in the period.

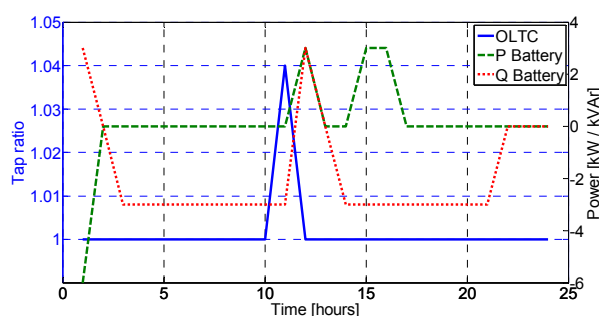


Figure 3: Schedule of assets within operating period

In order to analyze the forecast as well as the actual grid

management algorithm figure 4 shows its behavior with respect to switching applications. Most of the time the actual settings of the assets are kept constant since the assessment of the actual state is weighted with 1.1 as described above. Thus, the goal is not to invent a perfect forecast that should be valid in every situation and leads to an optimal grid state. Rather a grid management algorithm is achieved providing a valid grid state even facing voltage drops greater +/- 10% of nominal voltage.

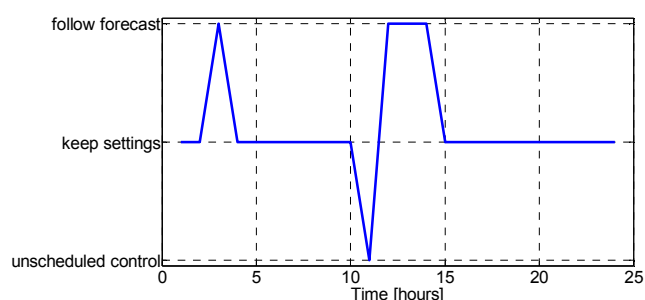


Figure 4: Schedule of assets within operating period

## CONCLUSION AND OUTLOOK

Future distribution grids will require a well-coordinated grid management in order to ensure a safe, reliable and autonomous grid operation. The proposed algorithm enables for an efficient grid management as well as an asset schedule forecast that can be derived out of the learned information. With respect to advancing smart grid development in the future, the required systematical coordination of DGs and other controllable assets can be realized through control strategies as presented in this paper.

To enable a spread of the algorithm an appropriate analysis of scalability and adaptability of the algorithm to other grid structures will be done [3]. The approach should be able to deal with new supply task in the future, when DG penetration increases as well as grid topology may be changing.

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