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Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming

Mohsen Nemati^{a,*}, Martin Braun^b, Stefan Tenbohlen^c

^a Siemens AG, Humboldt Street 59, 90443 Nuremberg, Germany

^b Fraunhofer IWES, University of Kassel, Kassel, Germany

^c University of Stuttgart-IEH, Stuttgart, Germany

HIGHLIGHTS

- Day-ahead dispatching of the renewable energy resources inside a microgrid.
- Genetic algorithm based optimizer for solving unit commitment and economic dispatch.
- Aging model of the Li-Ion battery based on an event-driven method.
- Mixed integer linear programming for optimal power flow of microgrids.

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ABSTRACT

Energy Management System (EMS) applications of modern power networks like microgrids have to respond to a number of stringent challenges due to current energy revolution. Optimal resource dispatch tasks must be handled with specific regard to the addition of new resource types and the adoption of novel modeling considerations. In addition, due to the comprehensive changes concerning the multi cell grid structure, new policies should be fulfilled via microgrids' EMS. At the same time achieving a variety of (conflicting) goals in different microgrids requires a universal and a multi criteria optimization tool. Few of recent works in this area have considered the different perspectives of network operation with high amount of constraints and decision criteria. In this paper two dispatch-optimizers for a centralized EMS (CEMS) as a universal tool are introduced. An improved real-coded genetic algorithm and an enhanced mixed integer linear programming (MILP) based method have been developed to schedule the unit commitment and economic dispatch of microgrid units. In the proposed methods, network restrictions like voltages and equipment loadings and unit constraints have been considered. The adopted genetic algorithm features a highly flexible set of sub-functions, intelligent convergence behavior, as well as diversified searching approaches and penalty methods for constraint violations. Moreover, a novel method has been introduced to deal with the limitations of the MILP algorithm for handling the non-linear network topology constraints. A new aging model of a Lithium-Ion battery based on an event-driven aging behavior has been introduced. Ultimately, the developed GA-based and MILP-based optimizers have been applied to a test microgrid model under different operation policies, and the functionality of each method has been evaluated and compared together.

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1. Introduction

The current worldwide power system transition towards a smart grid paradigm has invoked a wide variety of attempts to integrate environmentally friendly renewable energy sources (RES), distributed dispatchable generators (DDG), energy storage

devices, as well as demand side response (DSR) programs into distribution grids [1]. The huge amount of integrated distributed energy resources (DER) units and changes in energy demand introduce a new energy production-consumption pattern in the traditional structure of the energy systems, which results in miscellaneous operational challenges to guarantee balance, stability, predictability and efficiency in the power networks.

One attractive aggregation approach is the microgrid [2,3], which can be adapted to a wide variety of new power network types and market settings. Aside from its capability of switching

* Corresponding author.

E-mail addresses: mohsen.nemati@siemens.com (M. Nemati), martin.braun@uni-kassel.de (M. Braun), stefan.tenbohlen@ieh.uni-stuttgart.de (S. Tenbohlen).

Nomenclature

Acronyms

| | |
|------|------------------------------------|
| ASPM | adoptive SPM |
| BSS | battery storage system |
| CEMS | centralized EMS |
| DDG | distributed dispatchable generator |
| DER | distributed energy resource |
| DG | diesel generator |
| DOD | depth of discharge |
| DTX | Dynamic-Type crossover |
| ED | economic dispatch |
| EMS | Energy Management System |
| EOL | end of lifetime |
| FC | fuel cell |
| GA | genetic algorithm |
| GHG | greenhouse gas |
| LL | lifetime loss |
| MG | microgrid |
| MILP | mixed integer linear programming |
| MOP | microgrid operation policies |
| MT | micro gas turbine |
| OPF | optimal power flow |
| PR | P-Redispatching |
| PV | photovoltaic generator |
| RCGA | real coded GA |
| RES | renewable energy source |
| RESC | RES curtailment |
| SBX | Simulated Binary Crossover |
| SN | stress-number |
| SOC | state of charge |
| SPM | Semi-Probabilistic Mutation |
| TPX | two point crossover |
| UC | unit commitment |
| URC | unit recommitment |
| VSO | voltage set point optimization |
| WT | wind turbine |

Symbols

| | |
|--------------------|---|
| P_{FC} | electrical power of FC |
| v_{ci}, v_{co} | cut-in and cut-out wind velocity |
| v_r | rated wind speeds |
| α_k | externality costs of emission type k |
| β_{ik} | emission factor of generating unit i |
| K_{Ag} | SOC aging factor for each partial cycle |
| N_{Pos} | maximum number of possible cycles |
| W | weighting of different violation types |
| V_{io} | amount of violation |
| T_{amb} | ambient temperature |
| P_{STC} | module maximum power |
| E_M | incident irradiance of the modules |
| E_{STC} | irradiance under standard test conditions |
| T_M | temperature of the module |
| ε_{PV} | module-dependent proportionality constant |
| P_r | turbine rated power |

Variables

| | |
|--------------------|---|
| C_{BSS} | battery aging cost |
| P_{PV} | output power of PV plant |
| $P(v)$ | power output of wind turbine |
| $CF_{DG}(P_{DG})$ | operation fuel cost of diesel generator |
| P_{DG} | output active power of diesel generator |
| $CF_{FC}(P_{FC})$ | fuel cost for a fuel cell |
| $CM_{DG}(P_{DDG})$ | maintenance cost |
| $SUC(DDG)$ | startup costs |
| $SDC(DDG)$ | shutdown costs |
| CEM_{DDG} | cost of the environmental externalities |
| $C_{Ev}(t)$ | cost of event |

between grid-tied and islanded operation modes to enhance supply reliability, it also serves as a promising solution for coordinating stakeholder interests and improving network performance [4] such as congestion relief, voltage control, and loss reduction.

Aside from embedded component-level controls for facilitating island transition and stability maintenance, a large proportion of microgrid-specific functionalities should be realized by an onsite Energy Management System (EMS) [5], which not only serves as an economic optimizer but also monitors and adjusts power flows in the local network [6]. In comparison with their transmission level counterparts, microgrid EMS applications with economic optimization targets are generally faced with more stringent network and emission constraints [2,7]. In addition, such optimal resource dispatch tasks in microgrids—namely the unit commitment (UC) and economic dispatch (ED) problem—must also be handled with specific regard to the addition of new resource types (i.e. storage devices [8] and controllable loads [5] etc.) and the adoption of novel modeling considerations. In last years, many works have introduced interesting and practical concepts for intelligent dispatching of integrated DER in the microgrids. Xiaolong et al. introduce in [9] a building based virtual energy storage system model by utilizing the heat storage capability of the building, which is considered in a dynamic economic dispatch model of the microgrid. Boroojeni et al. present in [10] an oblivious routing economic dispatch algorithm for smart power networks, which focuses on the economic dispatch while managing congestion and mitigating power losses.

Due to different multi-facet complexity of the microgrid UC & ED problem, a large number of algorithms have been proposed in recent years to address this new field of interest. Almost all standard solution techniques for the classical UC problem have been further developed and partially adapted to the microgrid application settings, which include Lagrangian relaxation [11], mixed integer linear programming, and meta-heuristic methods such as particle swarm optimization [12] and genetic algorithm. Amini et al. investigate in [6] two decomposition methods namely Lagrangian Relaxation and Augmented Lagrangian Relaxation which are used to solve security constrained economic dispatch. Jingrui et al. present in [13] an optimal day-ahead scheduling model for a microgrid based on a hybrid harmony search algorithm. One of the promising novelties in the mentioned paper is the consideration of the power flow constraints in the optimization process. Luhao et al. propose in [14] an integrated scheduling approach based on robust multi-objective optimization, in order to minimize operation costs and emissions under the worst-case realization of uncertainties.

The GA based optimization methods have many advantages in comparison to other methods. They are commonly applied to solve different combinatorial optimization problems, which usually contain a high number of potential solutions that makes the application of enumeration techniques (e.g. dynamic programming lagrangian relaxation) problematical. Another promising advantage of the GAs is their flexibility and general applicability. The solution region may include continuous or disjoint areas feasible

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