Applied Energy 180 (2016) 672–681

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Operational scheduling of microgrids via parametric programming

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HIGHLIGHTS

- Modelling of microgrid system components.
- Formulation of optimal scheduling problem for energy management to minimize operational net cost.
- Parameterization of wind and solar energy resources to capture problem as a mixed-integer linear programming.
- Decoupling of solution dependency on weather forecast accuracy.
- Case studies used to analyse the solution framework through three different electricity pricing arrangements.

ARTICLE INFO

Article history:
Received 14 January 2016
Received in revised form 29 July 2016
Accepted 2 August 2016

Keywords:
Microgrids
Energy management
Renewable energy
Optimization

ABSTRACT

We present a parametric programming based approach for energy management in microgrids. An operational planning problem for a grid-connected microgrid with energy sources including solar photovoltaic, wind turbine and battery energy storage system, in addition to a household load demand, is captured as a parametric mixed-integer linear programming problem (p-MILP) through parameterizations of the uncertain coordinates of wind and solar energy resources. Thus, the energy management problem - typically nonlinear - is transformed into a linear bi-level optimization problem, where choice of the parameterization scheme is made at the upper level while system operation decisions are made at the lower level. The p-MILP formulation leads to significant improvements in uncertainty handling, solution quality and computational ease; by removing dependency of the solution on meteorological forecasts and avoiding the multiple computational cycles of the traditional online optimization techniques. The problem is solved offline on a flexible time-scale basis, allowing online implementation to be achievable on real-time system state updates. The proposed parametric programming approach extends the state-of-the-art in microgrid energy management methods and the results from various case studies are used to demonstrate the feasibility of our method.

1. Introduction

Energy is life to both current and future global economy. With the United Nations' estimate of world population growth at 74 million people per year, energy demand will continue to increase with human population growth and technological advancement. The International Energy Agency predicts that global energy demand will grow by 37% of the 2012 value, by the year 2040 [1]. Global energy usage and carbon emissions trends indicate an overall increasing tendency [2]. Therefore, concerns about climate change, cost of energy, efficiency and reliability of energy systems necessitate reshaping/upgrading of the global energy landscape to cope with present and anticipated environmental, economic and social needs.

Since most of the hydro resources in developed countries have been deployed [3], the evolving trend is to incorporate more non-hydro renewable energy resources into the energy generation matrix. Various studies forecast that electric power generation from renewable energy resources should almost triple by 2035; with wind and solar power accounting for 25% and 7.5% of the total power generation, respectively [4–6]. These predictions acknowledge that deeper penetration of renewables into the present power network would be achieved through the efficient integration and coordination of various energy harvesting devices (and storage systems) in such a manner that absorbs the inherent intermittency of renewable resources within the network.

Integration of such time-variable distributed or embedded sources in an electricity network calls for special considerations.

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http://dx.doi.org/10.1016/j.apenergy.2016.08.009
0306-2619/

Nomenclature

Indices

s	solar photovoltaic
b	battery
u	maingrid
w	wind turbine
t	continuous time
k	discrete time
i	microgrid component

Parameters

N	number of panels
η_g	instantaneous efficiency
η_{pt}	efficiency of power point tracker
η_r	solar panel reference efficiency
β_r	solar panel temperature coefficient
α	wind turbine friction coefficient
f_w	fractional availability of wind turbine rated power
C_p	power coefficient
η_b	battery efficiency
σ	battery rate factor
rf	scenario-grid resolution factor

Symbols

Q	realized net cost of microgrid operation (cents h^{-1})
Q^k	expected net cost of microgrid operation (cents h^{-1})
θ	parameterized renewable power (W)
$M_{i,k}$	net cost of system component i in time k (cents h^{-1})
$y_{i,k}$	activation state of system component i at time k (–)
h_i	depreciation of system component i (cents h^{-1})
c_i	component i operating and maintenance cost (cents W h^{-1})
e	electricity price (cents W h^{-1})
e_{pc}	electricity cut-price (cents W h^{-1})
P_{ub}	power buying from the maingrid (W)
P_{us}	power selling to the maingrid (W)
P_{b+}	charging power of battery (W)
P_{b-}	discharging power of battery (W)
L_1, L_2	primary and secondary loads, respectively (W)
SOC_{min}	minimum state of charge of battery (W h)
SOC_{max}	maximum state of charge of battery (W h)
SOC_b	battery state of charge (W h)
C_b	battery storage capacity (W h)
lt_i	lifetime of system component i (h)
DV_i	depreciated value of component i (cents)
E_+	charged energy of battery (W h)
E_-	discharged energy of battery (W h)
P_w	wind turbine power output (W)
ρ	air density (kg m^{-3})
A_w	area swept by wind turbine blades (m^2)
v	wind speed normal to turbine blades (m s^{-1})
v_{ci}	wind turbine cut-in speed (m s^{-1})
v_{co}	wind turbine cut-out speed (m s^{-1})
v_r	wind turbine rated speed (m s^{-1})
T_c	solar panel temperature (°C)
T_r	solar panel reference temperature (°C)
$NOCT$	solar panel normal operating temperature (°C)
P_s	solar photovoltaic power output (W)
A_s	surface area of a solar cell (m^2)
H	solar incident radiation (W m^{-2})

Typically, Distributed Energy Resources (DERs) consist of comparatively small-scale generation and energy storage devices that are interfaced with distribution networks and can satisfy the local consumption, or even export power to the surrounding network if generation surpasses the local consumption [7]. The interconnection of various energy sources and the information flows required for their integrated operation to reliably and securely supply electricity within a locality is what constitutes a microgrid [8]. A microgrid has assigned loads and energy storage devices, which support its operation in tandem or independently from a central grid [9]. Interactions with a central grid can be made possible through a point of common coupling, where the microgrid is connected to a central grid.

However, the implementation of microgrids faces many obstacles. Managing multiple generation sources and loads to meet the demand requirements and to maintain the microgrids stability, without exceeding any of the operating limits, is a complex task [10]. Consequently, efficient energy management is crucial to realizing many of the benefits associated with microgrids, so substantial research efforts have been devoted to developing methods and techniques for intelligent operation of microgrids within the larger electricity grid.

Energy management in microgrids can be considered as a large-scale optimization problem: given information on the current state of the system and (mostly uncertain) future changes in pricing, consumptions preferences, distributed generation potentials, and policies; the optimal decisions on how devices and systems should be operated are made [11]. Majority of energy management literature are concerned with operational scheduling of the constituent energy systems [8]. Frequently, the operational planning problem of a microgrid is formulated in mixed-integer linear programming (MILP) models, as in [12–17], which often have objective functions that may include cost or profit (continuous) functions and activation or deactivation (binary) decisions [4,18]. Inclusion of efficiency requirements via demand response and environmental conservation goals have become increasingly common [19–21]. The solution methods can be broadly divided into heuristic and deterministic routines. Heuristic methods allow for a reasonable solution to a difficult problem to be obtainable, albeit mostly at the expense of any systematic form of guarantee of optimality, as in [22–26]. Deterministic algorithms assume some level of understanding of the sources of system uncertainty; which makes the set of expected outcomes to be finite, thereby providing for closed form solution(s) of the problem to be attainable, as in [27–29]. However, some algorithms tend to combine both methods in practice, like in [30,31].

Furthermore, the potential for competing objectives and control challenges in microgrid coordination often necessitate the application of multi-objective optimization techniques and multi-level control architectures, as seen in [21,32–34]. Optimal operation problems have also been solved by embedding a non-model-based scheme, such as fuzzy logic or artificial neural networks, under an optimal power flow layer, as in [35–38]. This allows the training of the embedded layer with results from the optimal power flow problem [6]. In [15], some of the system state variables are captured as bounded uncertain parameters in a reactive scheduling framework. Nevertheless, to account for renewable resource variability, all the existing models either utilize a constant