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Optimal scheduling of a microgrid in a volatile electricity market environment: Portfolio optimization approach

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HIGHLIGHTS

- Kelly Criterion based strategy for operation of microgrids in a volatile electricity market.
- Elimination of the need for forecasting power generation and load demand in microgrid scheduling problems.
- Utilization of artificial neural network for electricity price forecast.
- Case studies are used to analyze the solution framework.

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ABSTRACT

This paper proposes an optimal scheduling strategy for a microgrid participating in a volatile electricity market. The microgrid system includes photovoltaic generators, a wind turbine, a load, grid connection, and a battery storage system. An optimal microgrid operation is achieved by maximizing the utility function represented by the exponential rate of growth of the electricity market value through electricity transactions between the microgrid and main grid, on the premise of satisfying the power balance and generation limit of system components. The uncertainties occurring during the microgrid operation are represented by generator output, load demand, and electricity price fluctuation. The proposed strategy utilizes the Kelly Criterion, an optimal strategy that maximizes the growth rate of an asset's net worth over repeated investments, coupled with an artificial neural network forecast of electricity price to deal with the volatile energy market. The proposed algorithm provides significant improvements in microgrid scheduling by eliminating the reliance on renewable generation and load forecasts, which makes it computationally inexpensive and thus feasible for real-time implementation. In representative case scenarios, using real-world tracers, we show that the algorithm has no dependency on meteorological forecasts and performs optimally in a volatile electricity market.

1. Introduction

The ever increasing electricity demand, climate change, and technology advances, is prompting the evolution of the centralized power grid to a distributed power network that has a higher efficiency of energy generation, integration, transmission, as well as distribution. Among all possible solutions [1–4], microgrids have shown their merit for having a high flexibility in terms of energy source selection and distributive characteristic. Renewable resources such as wind, solar and biomass are now widely utilized by microgrids [5–7]. In order to realize all the potential benefits of microgrids, efficient design strategies [8–11], as well as management strategies [12–15] should be in place.

The energy management of a microgrid consists of making optimal decisions with respect to microgrid sources, storage, as well as controllable loads, to satisfy demand and maximize profit by interacting with the main grid. Economic dispatch of a microgrid is more complex in comparison to the traditional electricity grid due to the intermittency of renewable energy sources, higher load fluctuations, as well as volatile energy markets [15–19]. For residential microgrids, profit maximization is of great interest as grid connection provides a revenue stream for the end users. Hence, the feasible profit opportunity has encouraged consumers to invest in large size generators to lower the Levelized Cost of Electricity [20,21] and consequently achieve shorter payback periods [22].

Substantial research efforts have been devoted to developing techniques for intelligent operation of microgrids within the larger electricity grid, which could enhance their reliability and profitability. The most prevailing challenge to microgrid modeling is the uncertainty

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Nomenclature

Sets and indexes

s	the path for electricity allocation
t	the time period used for optimization
ϕ	the order of a sample
r	reference target of microgrid

Parameters

Φ	number of sample
b	the rate of return for wining
f^*	the optimal betting fraction
l	the number of losses
N	number of repeating the investment
q	the probability for wining
w	the number of wins
T	the number of period of the scheduling horizon, h
t^0	the current period of the moving horizon, h
t^h	the end period of the moving horizon, h
E_t^{bat}	electricity stored in the battery during t, kWh
E_t^{buy}	electricity purchased from the grid during t, kWh
E_t^{load}	electricity sent to the load during t, kWh
E_t^{pv}	electricity produced from the generator during t, kWh
E_t^{sell}	electricity sold to the grid during t, kWh
η_c^{bat}	charging efficiency of battery storage
η_d^{bat}	discharging efficiency of battery storage
B_{max}	rated capacity of battery, kWh
B_{min}	minimum charged level of battery, kWh
Q^{bat}	levelized cost of energy storage, \$
Q_t^{buy}	electricity purchase price during t, \$
Q^{pv}	levelized cost of energy production for PV, \$
Q_t^{sell}	electricity sales price during t, \$
PF_t	profit earned during t, \$
G_N	exponential rate of growth for investing capital N times
$G_{s,t}$	exponential rate of growth for allocating electricity to target s at time t
V_0	initial capital, \$
V_N	capital after repeating an investment N times, \$
$V_{r,0}$	net worth of electricity that is allocated to reference target, \$
$V_{s,t}$	net worth of electricity that is allocated to target s at time t, \$
M	amount of electricity for allocation, kWh
W_r	unit net worth of electricity allocated to reference target, \$
$x_{s,t}^{\phi}$	the ϕ^{th} predicted relative rate of return for electricity allocated to target s at time t

Decision variable

$f_{s,t}$	fraction of electricity allocated through path s at time t

associated with the forecasts of renewable resources, user loads as well as electricity prices. Deterministic algorithms assume perfect forecasts for dominant sources of system uncertainties and consequently the obtained solutions may not be optimal [14,23,24]. Forecast models, such as Autoregressive (Integrated) Moving Average [25–28], Neural Network [29–31], Support Vector Machine [32,33] are often incorporated to overcome the issue associated with system uncertainties. The incorporation of forecast techniques gives more realistic solutions, but the feasibility of an algorithm becomes highly dependent on the forecast accuracy. The above-mentioned forecast models work well on a case-to-case basis, because energy consumption, meteorological information, as well as electricity markets, have high spatio-temporal variability. Therefore, it is crucial to consider prevailing uncertainties in the microgrid scheduling process. Stochastic programming [34–37], robust optimization [38–41], parametric programming [42], fuzzy logic [43], and other probabilistic approaches [44] have been utilized previously. Scenario-based stochastic methods have been widely studied [36,45]. Chance constraints have been employed to solve optimal power flow and scheduling problems at the transmission level [46,47]. Portfolio optimization techniques, such as conditional value at risk [17,48–50], provide a measure to quantify investment risk caused by system uncertainty. These approaches aim to reduce the impact from inaccurate forecasts as well as system disturbances, while more importantly, improve the generality of the models for a wider scope of microgrids with respect to their geographical location and configuration. However, coordination of multiple renewable energy resources in microgrid systems becomes very challenging. Developing forecast models for individual resources is time-consuming, while the complexity of an optimization model increases with the number of stochastic variables.

This paper presents a new strategy for optimal scheduling of a microgrid system in a volatile energy market. We adapted the Kelly Criterion, which is commonly applied in modern economics for managing portfolios of investments, to develop a new scheduling strategy suitable for microgrids participating in volatile electricity markets [51–54]. The approach maximizes the utility function of the long run asymptotic growth of investment while minimizing the expected time to reach arbitrarily large goals [51]. We show that when applied to a microgrid scheduling problem, the Kelly Criterion elegantly eliminates the dependency on the forecast of renewable energy generation as well as load demand, as it relies only on the forecast of the market electricity price over the predetermined horizon. This feature provides a great advantage for real-time implementation as online time-series forecasts are computationally taxing, and incorporation of several forecast models in an optimization model hinders its accuracy and practicality. We utilize an artificial neural network to forecast the electricity price. The efficacy of the proposed electricity market-based microgrid scheduling model is presented through case studies.

2. Microgrid system architecture

Fig. 1 depicts the configuration of the studied microgrid system. The microgrid consists of a wind turbine, solar panels, a load, grid connection and battery storage. In terms of electrical setting, the study assumes a single-node model and ignores transmission constraints [55]. The system can be represented by 6 state variables:

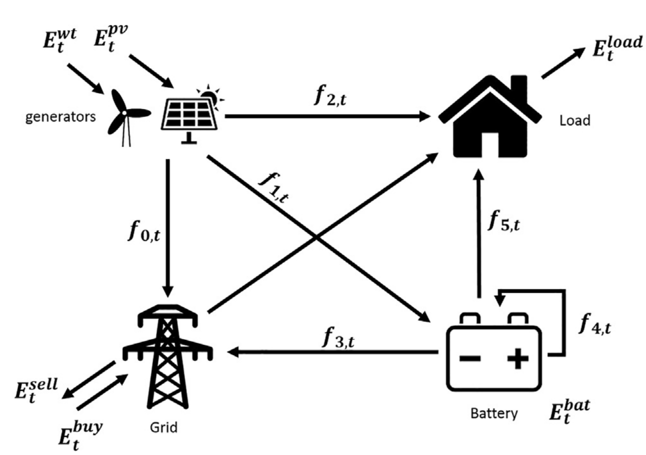

Fig. 1. Microgrid system schematic diagram.