Multi-Objective Optimal Fuzzy Energy Management for Grid-Connected Microgrid

Tiong Teck Teo, Member, IEEE, Xue Feng, Member, IEEE, Thillainathan Logenthiran, Senior Member, IEEE, Wai Lok Woo, Senior Member, IEEE, Khalid Abidi, Member, IEEE,

Abstract—This paper proposes a fuzzy logic based energy management system (FEMS) for a grid-connected microgrid with renewable energy sources (RES) and energy storage system (ESS). The objectives of the FEMS are reducing the average peak load (APL) and operating cost through arbitrage operation of the ESS. These objectives are achieved by controlling the charge and discharge rate of the ESS based on the state-of-charge of ESS, the power difference between load and RES, and electricity market price. The effectiveness of the fuzzy logic greatly depends on the membership functions. The fuzzy membership functions of the FEMS are optimized offline using a Pareto based multi-objective evolutionary algorithm (NSGA-II). The best compromise solution is selected as the final solution and implemented in the fuzzy logic controller.

Index Terms—energy storage management, membership function tuning, microgrid, multiobjective evolutionary algorithm.

I. INTRODUCTION

Microgrid are small-scale power system that consist of renewable energy sources (RES) such as photovoltaic (PV), wind power and load. The intermittency of the load and RES of a microgrid possess a serious challenge to the stability and security of the power system. The energy storage system (ESS) is seen as one of the keys enabling technology to mitigate these challenges. However, large-scale operation of ESS remains an expensive option despite efforts and subsidies from the government. As such, the operation of a single ESS should provide multiple services to maximize its benefit [1].

Several control strategies have been proposed for the energy management system (EMS) to operate the ESS such as fuzzy logic-based energy management system (FEMS) [2], fuzzy logic controller (FLC) for wind power smoothing [3] and grid power smoothing [4]. These methods improve the operation of the ESS, the design process heavily rely on expert knowledge and optimization is not applied.

Mathematical optimization methods such as mixed-integer linear programming (MILP), stochastic programming and convex optimization are also proposed. A day-ahead and week-ahead scheduling of ESS to maximize revenue is proposed in [5]. A bidding, scheduling and deployment of ESS solely for revenue maximization using stochastic programming is proposed in [6]. A daily cost minimization using convex optimization by considering a time-of-use tariff and day-ahead forecast of photovoltaic is proposed in [7]. These methods aim to maximize the revenue and does not operate in real-time. For the EMS of a microgrid, many factors have to be considered besides revenue maximization, such as peak demand reduction [8], storage degradation [9], and so on. The multiobjective of ESS in a grid-connected microgrid to significantly reduce the operating cost and power exchange is also investigated in [10].

Multiobjective optimization (MOO) of the EMS is proposed in [11]–[13]. The operating cost and peak shaving of the microgrid are formulated as a single-objective optimization problem through scalarization [11]. The hydrogen consumption of the fuel cells and load variation are minimized to prolong the lifetime of the fuel cell using FLC in [12]. The parameters of the FLC are tuned using genetic algorithm (GA). The economical cost and CO$_2$ equivalent emission formulated as a day-ahead unit commitment problem and is minimized using dynamic programming in [13]. While these methods are effective, it only produces a single solution and does not consider the trade-off between these objective functions.

In MOO, no single solution exists to minimize both objectives simultaneously. However, there exists a set of Pareto optimal solutions. A solution is part of the Pareto optimal solutions if none of the individual objective can be improved without deteriorating the other objective function. Without any additional information or preference, all Pareto optimal solutions are considered equally good [14].

Multiobjective evolutionary algorithm (MOEA) such as niched Pareto genetic algorithm (NPGA) [15], strength Pareto evolutionary algorithm (SPEA) [16] and nondominated sorting algorithm II (NSGA-II) [17] can find a set of Pareto optimal solutions in a single run. It has been used in induction machine design [18], generation and transmission expansion planning [19], [20] and electric power dispatch problem [21]–[23]. NSGA-II is able to find a more diverse solution on the Pareto-optimal front when compared to other multiobjective evolutionary algorithms [17].

Fuzzy logic-based energy management system (FEMS) are applicable in real-time to manage the intermittency of the load and RES. In the FEMS, the parameters such as the membership functions (MF) and its fuzzy rules are defined by expert knowledge. How to determine the optimal FEMS parameters remains a challenge. Moreover, parameter optimization algorithms for FLC only focus on a single objective function [24].

The main contribution of this paper is listed as follows:
1) the operating cost and peak demand of the microgrid are minimized simultaneously by tuning the membership functions of the FEMS using NSGA-II; 2) Multiple solutions are ob-
tained from the proposed methodology instead of one. The best compromise solution are selected as the final solution. This gives the decision maker the trade-off relation between two conflicting objective functions.

The rest of this paper is organized as follows. Section II gives the mathematical model of the microgrid and describe the proposed Fuzzy Energy Management System (FEMS), Section III provides the implementation of NSGA-II to optimize the fuzzy membership functions, Section IV provides the simulation studies and result. The paper is concluded in Section V.

II. PROBLEM FORMULATIONS

This paper considers the problem of operating an ESS which is connected to a microgrid with renewable energy generation capability. The time interval is the electricity market trading period. All system variables, constraints, and decisions are made at discrete time intervals of equal and constant length. The remaining of this section describes the mathematical model of microgrid and energy storage system.

A. Grid-connected Microgrid Model

An overview of a grid-connected microgrid test system is shown in Fig. 1. This microgrid is similar to those considered in [2], [10], [25]. It consists of PV and wind turbine, load and ESS. The RES and ESS are connected to a DC bus via a unidirectional and bidirectional DC/DC converter. The DC bus is then connected to the AC bus via a bidirectional DC/AC converter. The AC bus is then connected to the main grid and the AC load.

The power generated from wind turbine and PV panels are $P_{\text{wind}}$ and $P_{\text{pv}}$ respectively. Due to the intermittent nature of wind and PV power, the power generated may be more or less than actual load, $P_{\text{load}}$. The difference between the actual load and renewable energy is expressed as $P_{\text{balance}}$. A positive $P_{\text{balance}}$ means the actual load is more than renewable power generated and a negative $P_{\text{balance}}$ means the renewable power generated is more than actual load as shown in (1).

$$P_{\text{balance}}(t) = P_{\text{load}}(t) - P_{\text{wind}}(t) - P_{\text{pv}}(t)$$

This difference is compensated by the output power of the ESS, $P_{\text{ess}}$ as shown in (2). $P_{\text{grid}}$ is the resultant power that has to be met by the main grid.

$$P_{\text{grid}}(t) = P_{\text{balance}}(t) \pm P_{\text{ess}}(t)$$

B. Energy Storage System Model

Energy storage can be modeled by characterizing it in terms of power, energy ratings and efficiencies [26]. These characteristics are used to designed the ESS model in this paper.

1) Power and Energy Limits

The power limits can be expressed as follows.

$$0 \leq P_c(t) \leq \bar{P}_c$$

$$0 \leq P_d(t) \leq \bar{P}_d$$

where $\bar{P}_c$ and $\bar{P}_d$ are the maximum charging/discharging rate of the ESS. The maximum charging and discharging rate is considered in (3) and (4) in kW.

The energy limits of an ESS can be expressed as state-of-charge (SoC).

$$\text{SoC}_{\text{min}} \leq \text{SoC}(t) \leq \text{SoC}_{\text{max}}$$

where $\Delta t$ is the assumed to be the duration of trading period of the electricity market, in a fifteen-minute basis and SoC($t$) is in percentage.

2) Charging/Discharging Efficiency

$$P_{\text{ess}}(t) = P_c(t) - P_d(t)$$

$$P_c(t) = p_c(t)\eta_c$$

$$P_d(t) = p_d(t)\eta_d$$

where $p$, $\eta$ and $P$ are DC power, efficiency and AC power respectively. Subscripts $c$ and $d$ denotes charging and discharging. The energy losses during conversion between DC/AC and AC/DC is considered in (8) and (9). The net output power of ESS are considered in (7) in kW.

C. Fuzzy Energy Management System

A Mamdani type FLC has been used as an energy management system to control the charging and discharging rate of ESS. Fig. 2 shows an overview of the FEMS. It is a multi-input single-output FLC. The inputs are the power difference between the renewable energy sources and consumers’ demand, electricity market pricing and state-of-charge. These inputs are fed into the FLC to determine the charging and discharging rate of the ESS.

The proposed fuzzy energy management system aims to:

1) Energy arbitrage operation of ESS
2) Reduce the average peak load (APL) of the microgrid
3) Avoid over and under charging of the ESS by maintaining the SoC within a upper and lower limits

The first and second aims are achieved by discharging the ESS during high demand or cost period and charge during low
demand or cost period. The third aim is achieved by operating the ESS within the upper and lower limits. The proposed FLC is designed to reduce the consumers’ electricity bill and reduce the power exchanged between the main and microgrid. The detailed design of this FEMS is discussed in [10].

III. PROPOSED NSGA-II FOR TUNING OF FUZZY MEMBERSHIP FUNCTIONS

NSGA-II is fast and efficient in finding the Pareto-front compared to other multi-objective evolutionary algorithms such as Pareto-archived evolution strategy (PAES) and SPEA [17]. NSGA-II is used offline to optimize the location of the membership functions by minimizing the operating cost and APL of the microgrid while satisfying the constraints in Section II. The detailed implementation of NSGA-II is found in [17].

A. Chromosome design

The membership functions are coded as a string of real numbers as precision is lost when the solutions are coded in binary and changing to a neighboring solution require many bits change [27]. The chromosome design of the fuzzy membership functions are shown in [28].

B. Initial Population

The chromosomes are randomly generated and are subjected to the following constraints:

\[
\begin{align*}
\text{SoC}_{\text{min}} & \leq \text{SoC}(t) \leq \text{SoC}_{\text{max}} \\
P_{\text{balance}, \text{min}} & \leq P_{\text{balance}}(t) \leq P_{\text{balance}, \text{max}} \\
C_{p, \text{min}} & \leq C_p(t) \leq C_{p, \text{max}}
\end{align*}
\]

Constraint (10) is the upper and lower allowable operating capacity of the ESS. By operating the ESS within the boundary can prevent over and under charging. Constraint (11) and (12) are the maximum and minimum values of \( P_{\text{balance}} \) and \( C_p \) which are obtained from the historical data.

The maximum and minimum boundaries of these constraints can be modified to suit any storage technology, electricity market price and microgrid configuration according to the available historical data.

C. Fitness Function

The fitness function evaluates the quality of each chromosome in a particular generation. A poorly designed fitness function will result in a weak solution. The objective of the proposed FLC is to reduce the overall operating cost and APL by charging and discharging the energy storage at appropriate times. The overall operating cost of the microgrid can be calculated by (13).

\[
f_1 = \sum_{t=1}^{T} P_{\text{grid}}(t).C_p(t)
\]

where \( C_p \) is the wholesale electricity price. The microgrid can freely purchase and sell electricity from the main grid at time \( t \) at the same market price, \( C_p(t) \).

a) \( P_{\text{grid}}(t) > 0 \) if electricity is purchased from the grid;
b) \( P_{\text{grid}}(t) < 0 \) if electricity is sold back to the grid.

The APL of the power profile is calculated using (14). The operating cost can be reduced by reducing the peak load of the power profile as the price is relatively higher during such period.

\[
f_2 = \sum_{m=1}^{\omega} P_{\text{grid}, \text{max}}(m)
\]

where \( \omega \) is the total number of months.

The objective of the FLC is to minimize operating cost, and APL hence (13) and (14) are used as the fitness function to evaluate each chromosome.

1) Best Compromise Solution

Fuzzy set theory is implemented to determine the best compromise solution from the set of Pareto optimal solution [21]. For each nondominant solution \( k \), the respective fitness function is fuzzified using (15).

\[
\mu_i = \begin{cases} 
1 & F_i \leq F_i^{\text{min}} \\
\frac{F_i^{\text{max}} - F_i^{\text{min}}}{F_i^{\text{max}} - F_i} & F_i^{\text{min}} < F_i < F_i^{\text{max}} \\
0 & F_i \geq F_i^{\text{max}}
\end{cases}
\]

For each solution \( i \), the maximum and minimum values are \( F_i^{\text{max}} \) and \( F_i^{\text{min}} \) respectively. The normalized membership function \( \mu^k \) for each nondominant solution \( k \) is calculated using (16).

\[
\mu^k = \frac{\sum_{i=1}^{N_{\text{obj}}} \mu^k_i}{\sum_{j=1}^{M} \sum_{i=1}^{N_{\text{obj}}} \mu^j_i}
\]

where \( M \) is the total number of nondominant solution and \( N_{\text{obj}} \) is the total number of objective functions. The solution with the highest value of \( \mu^k \) is the best compromise solution.

IV. SIMULATION RESULTS AND DISCUSSION

The proposed FEMS is implemented using MATLAB/Simulink. The ratings of the grid-connected microgrid is shown in Table I. The data used in this paper are obtained from National Renewable Energy Laboratory (NREL) and wholesale electricity prices from Energy Market Company Singapore (EMCSG). A time series data from January 1, 2013, to March 31, 2014, are used in this paper. The data are sampled every 15 minutes. The resulting dataset consists of 43584 data points. The proposed FEMS aims to minimize the operating cost and APL from (13) and (14) of the grid-connected microgrid respectively by tuning the input fuzzy membership functions using NSGA-II.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV Array</td>
<td>13.68 kWp</td>
</tr>
<tr>
<td>Wind Turbine</td>
<td>12 kWp</td>
</tr>
<tr>
<td>Load</td>
<td>26.8 kWp</td>
</tr>
<tr>
<td>Energy storage capacity</td>
<td>90 kWh</td>
</tr>
<tr>
<td>Maximum charging rate</td>
<td>15 kW</td>
</tr>
<tr>
<td>Upper and lower limit</td>
<td>900kWh, 4kWh</td>
</tr>
<tr>
<td>Charging</td>
<td>discharging efficiency, ( \eta_c, \eta_d )</td>
</tr>
</tbody>
</table>

The proposed NSGA-II algorithm for tuning the membership functions are implemented using M-script file in MATLAB, and the FEMS is implemented in Simulink environment. All of the parameters required by GA/NSGA-II are determined through a heuristic approach and shown in Table II.
TABLE II: NSGA-II Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>P</th>
<th>G</th>
<th>λ</th>
<th>ψ</th>
<th>ρc</th>
<th>ρm</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
<td>100</td>
<td>40</td>
<td>2</td>
<td>0.9</td>
<td>0.05</td>
</tr>
</tbody>
</table>

where \( P \) is the total number of chromosomes, \( G \) is the total number of generations, \( \lambda \) is the number of selected chromosomes for crossover, \( \psi \) is the crossover parameter, \( \rho_c \) and \( \rho_m \) is the crossover and mutation probability respectively.

Three cases are studied in this paper. Case 1: Expert FEMS; Case 2: Standard GA Tuned FEMS; Case 3: NSGA-II Tuned FEMS. In case 1, the expert FEMS is from [10]. In case 2, the two fitness functions, \( f_1 \) and \( f_2 \), from (13) and (14) are normalized using (17) and sum into a single figure of merit using (18). Normalizing both objective before summing them up gives an equal importance to both objectives instead of using weighted sum where additional weights parameter have to be determined [29].

\[
X' = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{17}
\]

\[
f_{agg} = f_1 + f_2 \tag{18}
\]

The FEMS in case 2 and 3 are tuned offline with historical data from 1 January 2013, to 31 December 2013, and validated online with data from 1 January 2014 to 31 March 2014. Furthermore, the expert FEMS membership functions are added as one of the chromosomes in the initial population.

In case 2, the fittest solution of each generation is plotted onto the scatter heat map as shown in Fig. 3. It shows the convergence of the standard GA. Dark blue represents first generation, and dark red represents a hundredth generation. The optimum region is in the bottom left region of the heat map. From the first generation, the fittest solution of each generation improves and converges into the bottom left region through the genetic operators.

In FEMS optimized using NSGA-II, by comparing Fig. 4 and Fig. 3, case 3 have a more diverse Pareto front compared to case 2. It also shows the trade-off relation between the conflicting objective functions.

From Table III, the solutions obtained by different FEMS are fuzzified using (15) and (16) to obtain the \( \mu^k \). Among these solutions, Case 3: NSGA-II has the best compromise solution as it has the highest \( \mu^k \) of 0.65.

TABLE III: Best compromise solution for multi-objective optimization

<table>
<thead>
<tr>
<th>Case</th>
<th>Cost ($)</th>
<th>APL (kW)</th>
<th>( \mu_1 )</th>
<th>( \mu_2 )</th>
<th>( \mu^k )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Expert FEMS</td>
<td>4780.6</td>
<td>12.5</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Case 2: Standard GA</td>
<td>4666.2</td>
<td>12.5</td>
<td>1.00</td>
<td>0.00</td>
<td>0.35</td>
</tr>
<tr>
<td>Case 3: NSGA-II</td>
<td>4681.9</td>
<td>10.2</td>
<td>0.86</td>
<td>1.00</td>
<td>0.65</td>
</tr>
</tbody>
</table>

A. One day operation of FEMS using the best compromise solution

The best compromise solution from Section IV is used as the FEMS. Fig. 5 shows a one day operation of the FEMS. From 0000 to 0600 hours, \( P_{balance} \) is positive while the price is low. Hence the storage capitalized on this arbitrage opportunity to charge the storage. From 0800 to 1600 hours, \( P_{balance} \) and \( C_p \) begin to increase at simultaneously, as such the storage discharges to reduce the peak demand. From 1600 to 2000 hours, the evening peak demand kicks in and the storage continues to discharge. From 2000 to 0000 hours, the SoC of the storage is approaching the minimum SoC hence the discharge rate gradually decreases to prevent over-discharging of the storage. The \( P_{grid} \) power profile fluctuates less compared to \( P_{balance} \) as a result of FEM operation. The SoC of the storage also operates within the upper and lower boundary.

Electricity is costly during peak demand, by discharging during high price period also reduces the peak demand.
Reducing peak demand defers costly expansion of underutilized peaking power plant, transmission infrastructure, and distribution network. The APL is reduced by controlling the charging/discharging of the energy storage. In this manner, the consumption of the consumer can remain unchanged. The proposed methodology utilizes the real-time electricity pricing mechanism to enhance the operation of the current asset without affecting the consumption pattern of the consumer. It also does not require the intervention of the consumers to decide whether to buy or sell from the main grid. Furthermore, the proposed methodology utilizes the available resources without any changes or expansion to the current infrastructure of the microgrid. The proposed FEMS can be applied to other ESS operation as it is designed with historical data and parameters of the ESS.

V. CONCLUSION

This paper proposes a NSGA-II tuning of an expert FEMS. The objectives are to minimize the operating cost and APL of a grid-connected microgrid with real-time pricing. Expert knowledge is integrated into the initial population of NSGA-II to obtain a diverse Pareto front in a single run. Three case studies were conducted in this paper. Case 1 and 2 presents an expert and standard GA tuned FEMS respectively. Case 3 presents a NSGA-II tuned FEMS. The result shows that NSGA-II with expert knowledge in the initial population of GA is effective for handling multi-objective optimization with conflicting objective. NSGA-II is also able to obtain a diverse Pareto front. The proposed FEMS can be deployed to other power system with ESS with similar objectives as it is designed based on the historical data and not any specific storage technology.

REFERENCES