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## Article

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## Harnessing demand-side management benefit towards achieving a 100% renewable energy microgrid

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### Abstract

Optimal sizing with energy management strategy as a transition pathway towards a sustainable 100% renewable energy-based microgrid is investigated in this paper. Due to the challenges of intermittency of renewable energy, microgrid operations are complicated. Hence, in order to overcome some of the challenges facing microgrid planning and operations, optimal capacity sizing incorporated with energy management strategy considering time-ahead generation prediction is proposed. The system model consists of wind turbine (WT), solar photovoltaic (PV) and battery energy storage system (BESS). The generation forecasting output is used to reschedule the flexible demand resources (FDR) to reduce the mismatch between power demand and supply, and optimal sizing of components is performed jointly to determine the optimal capacity values of the PV, WT, and BESS for minimal investment costs. The optimization results for the scenarios with and without load shifting effects of FDRs are determined and analyzed for the case study. From the results obtained, the application of demand scheduling program using the generation forecasting outputs resulted in a cost-saving of 12.41%. The forecasting model is implemented using a random forest algorithm on python platform and the mixed-integer linear program on MATLAB<sup>®</sup> environment is used to model and solve the capacity sizing problem.

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**Keywords:** Flexible demand resources (FDR); Random forest (RF); Wind turbine (WT); Photo-voltaic (PV); Battery energy storage (BESS)

### 1. Introduction

Optimal component sizing is a crucial aspect of long-term planning towards maximizing the technical and economic benefits of power systems. The design specifications for sustainable, reliable and 100% renewable energy based-microgrid development has necessitated the incorporation of demand-side management (DSM) for maximum

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benefits. This can further be enhanced by introducing energy resource forecasting into the energy management strategy and component sizing models as presented by Amrollahi and Bathae [1]. As the share of wind and solar energy resources increases system resilience decreases as highlighted by Alizadeh et al. [2]. This is due to the stochastic nature of wind and solar power generation, which varies with the weather changes; this necessitates the incorporation of an efficient energy storage system. However, a system that considers only energy storage as a source of flexibility tends to be very expensive. Sheth et al. [3] states that there is a need for the inclusion of DSM and renewable energy generation forecasting in the microgrid planning and operation. The implementation of the DSM programs has the potential of acting as an additional modality towards meeting the net-load as well as minimizing the total investment cost of the microgrid, through customers' participation.

The cost–benefit advantage of incorporating the short-term forecasts of solar irradiance, wind speed and load demand as a cost-effective approach in reliable system operation planning is highlighted in [4]. Hodge et al. [5] asserts that a precise outlook into the expected generated power profile can provide the necessary flexibility planning for the operator to intelligently schedule the various system components, especially the loads. The economic benefits of DSM in terms of energy market planning and demand flexibilities using demand response is also discussed in [6]. Hence, optimal scheduling of flexible demand resources (FDRs) within the microgrid system can yield enough operational flexibility from the demand side. This benefit can ultimately be reflected in the economics of storage capacity sizing and cheaper cost of electricity for the end-user. However, the appropriate implementation of DSM, especially for optimal scheduling of FDRs can be effectively achieved with the knowledge of future generation capacity of the renewable energy systems. With the forecasted generation information, the client can alter their energy demand to benefit from the flexible pricing provided by the utilities, in order to reduce their energy consumption bills.

This paper investigates an optimal component sizing and energy management strategy towards achieving 100% renewable energy-based microgrid. The scheme under consideration consists of the WT and PV as the energy-generating sources alongside the BESS. The potential benefit of the energy management strategy is evaluated by its effectiveness in addressing the variability of the renewable sources as well as the cost–benefit analysis of the optimal component sizes. The sizing optimization problem was solved using the MILP solver in MATLAB®, and resource forecasting was done using Scikit-learn tools in Python.

## 2. Description of case study and system modeling

The energy management strategy discussed in this study is implemented for a Kenyan microgrid in Marsabit county, and the proposed system consists of wind generator, solar PV and BESS as shown in Fig. 1 and the system parameters for BESS, WT and PV are as summarized in Table 1. The operation of FDRs (shiftable loads) tries to minimize the gap that exists between the electricity generation profile and consumption based on the DR strategy. The FDRs are activated to consume surplus generation and are deactivated during periods of shortages.

### 2.1. Photo-voltaic system model (PV)

The generated power output  $PV_p$  of the PV system in kW with respect to the received solar irradiances  $R$  in ( $W/m^2$ ) can be determined by using Eq. (1).  $\eta_{pv}$  is the PV module derating factor,  $R_{stc}$  is standard solar irradiance and  $PV_r$  is the rated capacity in kW.

$$PV_p(t) = PV_r(t) \times \eta_{pv} \times \frac{R(t)}{R_{stc}} \quad (1)$$

### 2.2. Wind turbine model

The wind turbine generated power output depends on the speed of the wind at specified hub height. The power output of a WT can be described by using a piece-wise function as expressed in Eq. (2).  $WT_r$  is the rated output power;  $w_{cin}$ ,  $w_r$  and  $w_{cot}$  are the cut-in, rated and cut-out wind speeds, respectively.

$$WTp(t) = \begin{cases} WT_r \times \frac{w(t)^3 - w_{cin}^3}{w_r^3 - w_{cot}^3} & w_{cin} \leq w \leq w_r \\ WT_r & w_r \leq w \leq w_{cot} \\ 0 & w < w_{cin} \text{ or } w > w_r \end{cases} \quad (2)$$

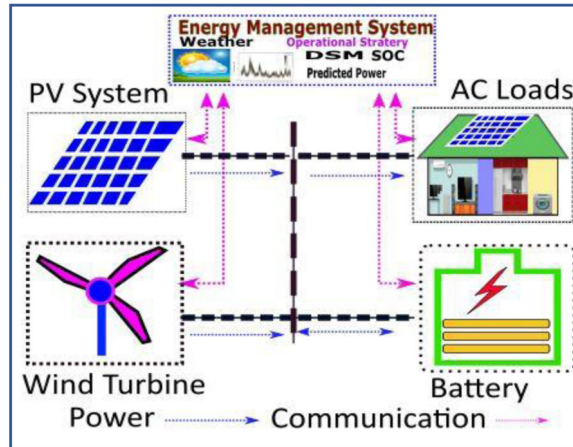


Fig. 1. Proposed microgrid configuration.

Table 1. Simulation parameters for the proposed system.

Parameters	
Discount rate, $r$	5%
Inflation rate	6%
Rated power	1 kW
Investment cost	1690 US \$/kW
PV maintenance & operation costs	26 US \$/kW/yr
PV reduction factor	84%
PV lifetime	25 yr
WT rated power	1 kW
WT investment costs	2030 US \$/kW
WT maintenance & operation costs	76 US \$/kW/yr
Cut-in wind speed	3.5 m/s
Rated wind speed:	14 m/s
Cut-out wind speed:	25 m/s
BESS investment costs	300 US \$/kW
BESS maintenance & operation costs	10 US \$/kW/yr
Efficiency	85%
Lifetime	5 yr

### 2.3. Battery energy storage system (BESS)

The BESS state of charge at any given time  $t$  is a subject the difference between the system load and the sum of the total renewable generation with reference to the previous state of charge. The BESS amount of charge at any given time  $t$  for the charging (in the event of generation surplus) and discharging (in the event of generation deficit) operation state are given by Eqs. (3) and (4), respectively.

$$SOC(t) = \left( PVp(t) + WTp(t) - \frac{PL(t)}{\beta_v} \right) \times \beta_{ec} + SOC(t - 1) \times (1 - dh) \tag{3}$$

$$SOC(t) = - \left( \frac{PL}{\beta_v} - [PVp(t) + WTp(t)] \right) / \beta_{ed} + SOC(t - 1) \times (1 - dh) \tag{4}$$

where  $SOC(t)$  and  $SOC(t - 1)$  are the state of charge of the BESS for the current and previous time period in kWh respectively,  $dh$  is the hourly rate of self-discharge,  $PL$  is the load demand,  $\beta_v$  is the efficiency of the inverter and  $\beta_{ec}$ ;  $\beta_{ed}$  are the BESS charging and discharging efficiency.

### 3. Wind and solar forecasting

The wind and solar power forecasting model considered the following input parameters [7]; wind speed, solar irradiance, humidity, temperature, pressure and wind direction. The Random forest (RF), regression forecasting approach, is adopted in this study as explained below. RF is a bagging ensemble-based machine learning algorithm that combines several single models of classification and regression trees. The RF has the advantage of overcoming the shortcomings of the classical decision tree, which are over-fitting of the training data and high variance by randomization procedures [8]. The details of training and implementation procedures for the RF algorithm are discussed in [9]. The prediction results of the forecasting models are evaluated using the mean absolute error (MAE), root means square error and the  $r^2$  metrics [10].

### 4. Demand-side management and flexible demand resources

Demand-Side Management (DSM) programs are procedures that attempt to modify the energy demand of the power system in order to improve the overall system efficiencies. Based on appropriate DSM, the FDR can be activated to consume surplus power during the period of excess generation and deactivated during periods of low generation. Netload demand after DSM implementation is equal to the initial load demand PL, plus the FDR capacity defined as SD.

$$PL'(t) = PL(t) + SD(t) \quad (5)$$

### 5. Sizing optimization: objective function and constraint

The objective of the optimum component sizing is to minimize the Net Present Value (NPV) of the total investment costs (TIC). The investments cost entails the capital costs, operation and maintenance and the replacement costs of PV, WT and BESS. The optimization decision variables are optimum component sizing of PV, WT and BESS.

$$TIC_{NPV} = C_x + (O\&M_x + RP_x - RV_x) \sum_{t=1}^T \frac{1}{(1+r)^t} \quad (6)$$

where the subscript (x) represents each component of the microgrid.  $C_x$  is the capital investment costs;  $O\&M_x$ ,  $RP_x$  and  $RV_x$  represents the operation and maintenance costs, replacement costs and the salvage value respectively.  $r$  is the discount rate,  $t$  is the time period index and  $T$  is the project lifespan. The system constraint is such that the total power generated should satisfy the demand at any given time, with and without FDR, as illustrated by Eq. (7).

$$PVp(t) + WTp(t) + P_b^{ds}(t) - P_b^{ch}(t) = PL'(t) \quad (7)$$

### 6. Simulation results and discussion

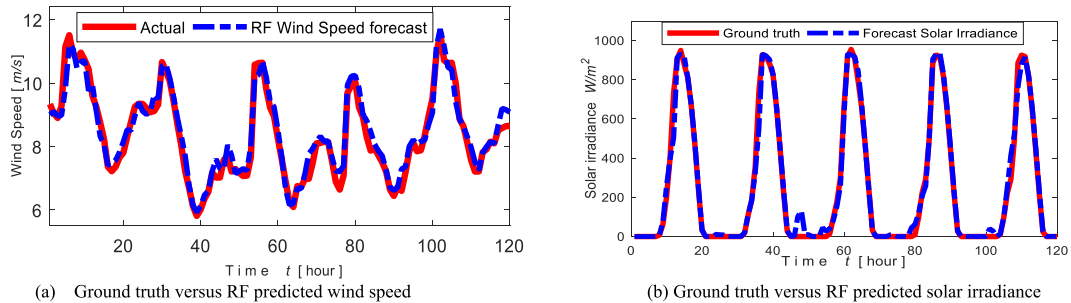
The forecasting results based on MAE, RMSE and  $r^2$  performance metrics for wind speed, solar irradiances, wind and solar photovoltaic power are as summarized in Table 2. The performance of the RF algorithm depends on the selected size of the estimators.

The number of estimators  $n$  represents the numbers of decision trees selected and grown at random with replacement during the training phase of the model. As it can be observed, the best performances are obtained when the decision tree is set to 800 for the case of wind speed and wind power prediction. This is confirmed by the least error values indicated by the MAE and RMSE error metric values for wind speed and wind power forecast results. The appropriateness of the model and parameter estimation selection are validated by the highest value of the  $r^2$  metric. Fig. 2(a) and (b) show a graphical comparison of the actual versus the predicted data using the RF forecasting model.

The sizing optimization results for microgrid component size for two cases is presented in Table 3. The optimal minimum total investment cost without DR is US \$ 15,247,276.77 for the obtained optimal component sizes. The large optimal capacity of the BESS is selected by the optimization program to compensate for the huge power mismatch between load demand and generation. For case 2 simulation (with DR), the total investment cost is US \$ 13,355,165.67 with the optimal system component sizes indicated in Table 3. The application of the DR

**Table 2.** Random forest forecasting simulation results in terms of performance evaluation metrics.

Predictions	Error metrics	$n = 8$	$n = 80$	$n = 800$
Wind speed	MAE (m/s)	0.28	0.26	<b>0.24</b>
	RMSE (m/s)	0.38	0.34	<b>0.31</b>
	$r^2$	0.93	0.93	<b>0.95</b>
WT power	MAE (kW)	42.91	39.31	<b>37.68</b>
	RMSE (kW)	62.14	53.63	<b>52.28</b>
Solar irradiance	MAE (m/s)	17.85	<b>19.48</b>	20.63
	RMSE (m/s)	47.10	<b>42.36</b>	440.6
	$r^2$	0.98	<b>0.98</b>	0.98
PV power	MAE (kW)	31.59	<b>22.09</b>	23.40
	RMSE (kW)	53.42	<b>48.05</b>	49.97

**Fig. 2.** Show a graphical comparison of the actual versus the predicted data using the RF forecasting.**Table 3.** Results comparison for without and with DSM scheduling consideration.

Scenario	Without DSM	With DSM
Demand side management	None	FDR scheduling
WT size kW	2054	1866
PV size kW	1196	1401
BESS size kWh	7150	5200
BESS cost (US \$)	6.30E+06	4.58E+06
BESS % cost proportion to total costs	41.33%	34.31%
Investment costs (US \$)	1.52E+07	1.34E+07
% investment reduction	–	12.41%

program for FDR rescheduling results in a significant cost-saving in the investment costs of about 12.41%. The DR implementation allowed the customers to time shifts the operation of the FDRs from the period of deficit generation to surplus generation periods resulting in a percentage cost reduction proportion of the BESS to total investment from 41.32% to 34.31%. The increase in PV capacity and decrease in WT is because PV costs are relatively cheaper compared to WT generation technology for the considered region.

## 7. Conclusion

In this paper, an optimal sizing and energy management strategy for the design of a 100% renewable energy-based microgrid has been investigated using DSM and resource forecast. The DSM approach tries to shift the operation of controllable loads (FDRs) to coincide with the period of surplus generation and to minimize energy gaps between the demand and generation. The results of the forecasting were used to improve the planning and effectiveness of the FDR scheduling program. The optimum component sizes were evaluated with and without the FDR scheduling program. From the simulation results obtained, the application of the FDR scheduling DSM program significantly reduced the investment cost by about 12.41%. There is also a percentage cost reduction proportion of the BESS to total investment from 41.32% to 34.31%. This paper has demonstrated the potential cost-benefit of consideration

of DSM in optimum component sizing towards achieving a 100% green microgrid for the considered case study. The strategies described in this work can be adopted for other regions.

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