Short-term Operation of a Hybrid Minigrid under Load and Renewable Production Uncertainty

Davide Fioriti, Romano Giglioli, Davide Poli
Department of Energy, Systems, Territory and Construction Engineering
University of Pisa
Pisa, Italy
Email: davide.fioriti@ing.unipi.it

***Abstract*—Properly sized and operated hybrid minigrids can assure good-quality electricity to rural households at an affordable price. A system composed by renewable sources, a diesel generator and batteries can be a cheaper option, but it requires daily operation in order to reduce fuel consumption, to assure fuel availability, and to avoid quick degradation of the batteries. Variability in load and renewable generation introduces uncertainties that must be considered in order to assure a proper operation, thus reducing the curtailment of both load and renewable production. This paper proposes a procedure for short-term operation of a hybrid minigrid in order to cope with errors in forecasting of both load and renewable generation. A probabilistic tool based on Monte Carlo simulations and mixed-integer programming is developed to estimate the optimal working point of the diesel generator and batteries. The Monte Carlo scenarios are singularly optimized, thus defining several optimal schedules that are combined to define the proposed stochastic commitment and dispatchment. The methodology is supported by numerical case studies that even confirm the applicability of Monte Carlo simulations to the short-term operation.**

***Keywords*—off grid; Monte Carlo; MILP; unit commitment; economic dispatch**

I. INTRODUCTION

Energy poverty in developing countries is a huge hurdle in the world. According to IEA, 1.2 billion people still lack in electricity access and even more in access to good cooking facilities [1]. Almost the totality of them are located in Sub-Saharan Africa and in the so-called developing Asia [1]–[3]. Rural areas are the poorest and the living conditions are much worse than in urban areas. The quality of life in those areas is very poor; they have low income, scarce healthcare, lack in clean water access, and high illiteracy rate [2], [4]. In addition, their basic needs like lighting, cooking, listening the radio, and the recharge of the cellular phone are often supplied by very costly, unhealthy, polluted, and low quality energy such as biomass, kerosene, paraffin, batteries, and diesel. Only few people own a small television and even less a small fridge [2], [3], [5].

Many countries and international agencies developed policies in order to address this hurdle, especially in providing access to electricity, privileging more populated areas, with higher energy demand, in the nearby of the existent national grid [2], [3], [6], [7]. High population density causes high-energy demand that shortens the payback time of investments in distribution grids. Instead, the higher the distance of the community from the grid, the higher the distribution costs and the payback time. Conversely, rural areas can be very low populated, dispersed, and far from the existent grid, thus raising the grid costs more than the energy demand. In some of those areas, grid improvements can be so expensive that off-grid systems such as home systems or mini-grids are preferable [3]. According to IEA reports, achieving the universal electricity access by 2030 to rural people requires off grid solutions for the 70% of cases, whereof 65% minigrids and 35% home systems [8].

The majority of the home systems are designed to supply single and dispersed household with basic needs of few tenths of watt [9], [10] but some more powerful systems can supply buildings like small hospitals or municipal buildings [2]. The electricity quality is usually low and limited to some hours per day. Minigrids, instead, supply more densely populated area though a local distribution grid not connected to the national one. The size of each minigrid ranges from few kilowatts up to some megawatts, potentially with a good quality vector and a 24/7 service, thus enabling the development of the industrial and commercial sector [2].

Minigrids are being used in remote areas or islands, but they rely mainly on inefficient and polluted diesel generators [2]; only few 2-3% of them are hybridized with renewable energy sources [9]. Diesel generators are flexible and dispatchable with low capex costs, but they need to be often replaced (3-4 years at continuous service [7]), and they have very high operational costs due to the fuel supply and maintenance. The more remote the village, the higher the fuel transportation costs and the difficulties to obtain spare parts. In addition, diesel generators in rural areas usually work at low load for many hours per day, reducing the efficiency and raising the maintenance costs. Renewable energies, instead, require higher capex costs, especially when batteries are used, but they can reduce the operation costs and be a cost-effective solution, as highlighted by papers and international agency reports [2], [7], [11]. Conversely, renewable sources are mostly fluctuating and unpredictable, so they require to be coupled with a controllable source like batteries or a fuel generator. Diesel generators, in fact, can offer a flexible backup source to supply the load during shortage of energy from renewable sources or batteries. Fuel cells could constitute an interesting option; nevertheless, in this environmental and social framework their reliability and maintenance issues could be a serious concern. In addition the couple fuel cell-electrolyzer consumes water, a valuable good in rural areas, and has both low round-trip efficiency and low life expectancy.

A hybrid system with a diesel generator must be optimally operated in order to reduce the consumption of the costly fuel and, thus, the diesel shortage. Operation of power systems is commonly characterized by the following horizons:

- Long-term operation: it guarantees the proper upgrading of the system in 10-20 years, in order to maintain the system reliability and quality [12].
- Medium-term operation: it spans from several months up to a year to manage the maintenance, the fuel procurement, and the usage of big reservoir.
- Short-term operation: it guarantees the real time load balance, and it handles both unit commitment (UC) and economic dispatching (ED).

Due to the high penetration of renewables, many papers [13]–[15] address uncertainties in renewable and load in ED and UC through several methodologies, including stochastic unit commitment, interval unit commitment, robust unit commitment and hybrid unit commitment [16]. The optimization horizon can vary from some minutes to days. Recently, rolling horizon strategies are leading to better address the uncertainties in renewable production and load [16]–[18].

Different mathematical approaches are available to solve UC and ED problem [17], [19]. Mixed-integer linear programming (MILP) is the standard approach [18] and guarantees the global solution, but the computing time increases sharply with the problem size [20]. When the problem size rises, decomposition techniques or Lagrangian relaxation can be applied, reducing the mathematical burden [21].

Several stochastic problems rely on at least one expectation operator to cope with uncertainties [17], [22]. Scenario-based approaches using Monte Carlo simulations can address this goal [17], [21]–[24], but the method requires a number of scenarios to converge, raising the computational costs [17]. Thus, some papers use scenario reduction techniques [17], like WILMAR [16], [18] or k-means [25], in order to reduce the computational time. Other papers, instead, do not use scenario reduction techniques, but the computational time is still low [26]. Sample Average Approximation technique can estimate the expectation value for the stochastic problem, averaging the optimization costs for each scenario [17], [26].

This paper presents a short-term stochastic optimization model for a rural diesel-PV-battery hybrid minigrid, minimizing the fuel consumption and emission, while enhancing the system quality and enabling income generating activities of the community. A day-ahead model with Monte Carlo simulations is used in order to cope with uncertainties in both renewable production and load, and the mathematical formulation is MILP. According to our literature review, the major novelties of the paper are:

- A new stochastic model able to cope with uncertainties in renewable production and load in rural minigrids.
- A new Monte Carlo approach to short-term operation able to reduce the complexity of a classic stochastic model including unit commitment and economic dispatch rule.
- Numerical simulations supporting the methodology.

The remaining sections of the paper are organized as follows. Section II describes the model structure, Section III details the mathematical formulation, and Section IV reports a numerical case study. Finally, Section V illustrates the conclusions and the future research activities.

II. Problem formulation

A. Minigrid system

Minigrids can rely on the following three main configurations [2], [7], [26], [27]:

- AC Bus: whole generation is coupled at the AC busbar.
- DC Bus: a DC busbar is available and whole electricity generation is coupled at this level.
- Hybrid: in this configuration, electricity generation is coupled to both the DC and AC busbar.

According to The Alliance for Rural Electrification (ARE), the choice between the three configurations is related to several technical, geographical, and socio-economic factors related but not limited to load profile, renewable sources available, and the distribution grid [2], [7].

Very low load demand can be supplied by completely DC grids without AC loads, as in the case of several villages in India with grids in the range of 200-1200W [28]. For standard households, industrial, and commercial applications, AC grids are preferable, at present, due to the scale and price of AC appliances [29], and to the higher costs for DC converters and protection [30]. Future expectations see an inversion of the process, due to the higher efficiency the DC grid can introduce into the power system [31]. Some renewable sources supply directly the DC voltage level; electromechanical generators often supply power at AC level, but using a converter to supply at DC voltage can lead to higher the system efficiency.

For a wide-ranging approach, we assume a diesel-photovoltaic-battery system, based on AC bus as in Fig. 1. This configuration allows the decentralization of generation units enabling a better location of each unit according to the site requirements. For example, diesel generator may be placed farer from the community reducing the negative impact of noise and pollution, while renewable units can be placed where the availability of the resource is higher.

Several battery technologies are used in rural minigrid. Lead acid battery is the most common choice due to the low investment cost, high robustness, and simplicity. Nevertheless, the working temperature, the charge and discharge current, and the depth of discharge affect heavily the battery life [32]. This leads to oversize the battery in order to satisfy the cycle life requirements, but the costs rise. Several other technologies are rising interests for rural application, such as the NaCl [33], vanadium redox [34], lithium [35]. Lithium batteries have high value of cycle life, power and energy density, and efficiency,

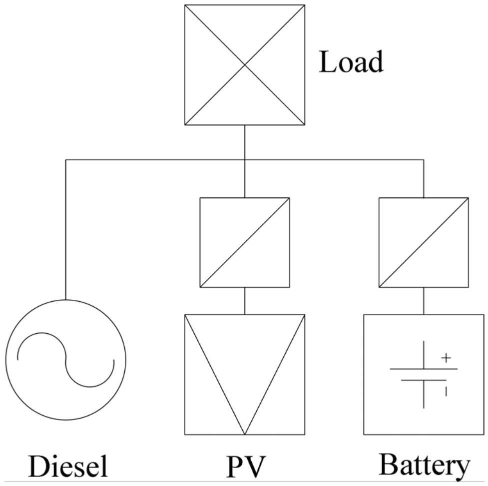

Fig. 1. Mini grid configuration.

but they are expensive [19], [36]–[38]. In addition, a charger controller is required to assure the stability, also allowing remote monitoring [32]. High energy density allows reducing weight and volume of components, thus leading to simplify the transportation and save in both construction and shipping costs. Since studies evaluate lithium batteries as promising for off grid applications [37], we assumed the use of this kind of storage.

B. Renewable energy availability and load forecasting

A proper forecasting method for load and renewable energy availability is crucial to efficiently operate a minigrid. In fact, forecasts allow reducing the fuel consumption, setting a cost-effective unit commitment, and, in case of lack of generation, defining a load curtailment program that minimizes the negative effects of the energy shortage. Load forecasting is commonly subdivided in long-term, medium-term, and short-term, similarly to the operation horizon. For the purpose of the paper, the focus is on short-term.

Several techniques have been developed such as time-series, artificial intelligence, expert systems, etc. [39]–[41]. Inputs for the forecast are temperature, humidity, hour of the day, type of the day (working or non-working), past load and renewable availability, and so on. Such techniques usually require a database in order to train the method.

A few papers perform short-term load forecasting in isolated and rural context. The errors might be significant due to the high variability of the community consumption in the early stages of electrification. In addition, it is difficult to obtain data from the area and develop an estimation method.

In the present paper a loading forecast method is assumed that estimates the load and renewable availability profile for the next 24 hours. In addition, the errors in load forecasting are taken into account in the stochastic method through a Gaussian probability density function.

C. Stochastic formulation

A classical two-stage stochastic linear problem has the following objective function [42]:

$$\min\left\{c^T x + \mathbb{E}\left[\min\left\{q(w)^T y(w)|\xi\right\}\right]\right\} \quad (1)$$

Variables x and c are respectively the state variable and cost vector of the outer problem, while y and q are the state and cost variable for the inner problem related to a given realization w, and ξ is a random vector. The outer problem usually manages the decision variables for slow response units, while the inner problem for faster ones.

Sample Average Approximation applied to (2) considers a pool of scenarios $\{\xi_i\}$ to approximate the feasibility set for the stochastic variables. The estimation operator is approximated with the average cost of the inner optimization [26].

$$\min\left\{c^T x + \frac{1}{N_s}\sum_{i=1}^{N_s}\min\left\{q(w)^T y(w)|\xi_i\right\}\right\} \quad (2)$$

The proposed approach, instead, optimizes the UC and ED for each single scenario leading to a set of optimized solutions. Later, the solutions are post-processed and synthesized, thus defining the unit commitment and economic dispatch for the following 24 hours.

Our model captures the stochastic nature of the load and photovoltaic production using a set of scenarios generated through Monte Carlo simulations. Firstly, the time profiles are generated. Secondly, for each scenario a mixed-integer linear programming method optimizes the diesel unit commitment and economic . Finally the whole solutions for each scenario are synthesized, thus defining the UC and the power level when the diesel is operating. Fig. 2 shows the optimization decision process. The synthesis criteria are as follows:

1) Unit commitment: For each hour, we evaluate the expectancy of the diesel state, and we identify the diesel UC as the most occurring state between the optimized solutions.
2) Power level: For each running hour, we define the diesel power level of the UC as the average of the optimized solutions evaluated by the proposed model.

Our model is an extension of [24] for isolated minigrids with different criteria to set the UC and power dispatching of the diesel generator. That criterion defines the power UC as the average value of the dispatched power in the considered Monte Carlo scenarios. Our approach, instead, considers firstly the unit commitment decision, and later the power level issue, thus reducing the diesel working hours and raising the efficiency of the unit. In rural minigrids with high renewable energy penetration and storage [43], the diesel generator works few hours per day to enhance the efficiency of its working point according to constraints. Thus, low cost UC is very important, and our model stresses this goal.

III. Mathematical formulation

This section describes firstly the optimization of the single scenarios and then the stochastic model.

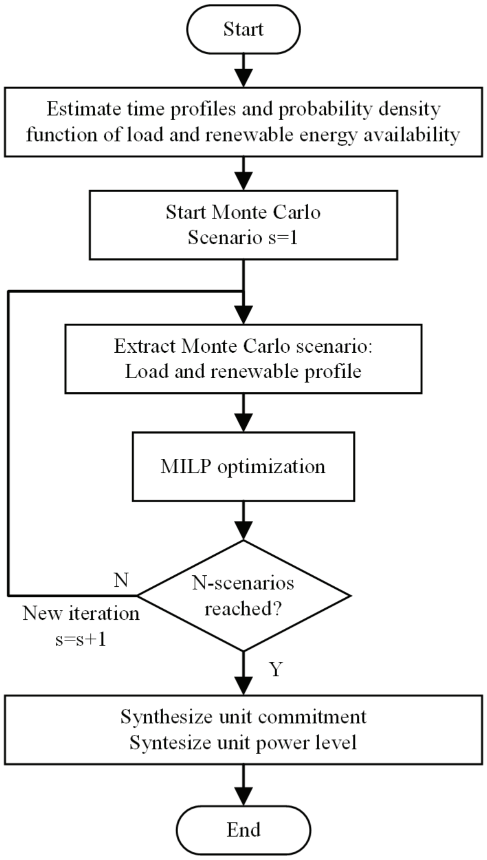

Fig. 2. Optimization flow for the proposed stochastic model.

A. Single scenario formulation

1) Diesel: Diesel generator constraints are the maximum and minimum generation levels. The cost function is linearized in N_p sections:

$$\forall t \qquad P_{D,t} = \sum_{i=1}^{N_p} P_{Di,t} \tag{3}$$

$$\forall t \qquad C_{F,t} = \sum_{i=1}^{N_p} c_{F,i} P_{Di,t} \tag{4}$$

$$\forall i,t \qquad z_{Di,t} P_{Di,min} \le P_{Di,t} \le z_{Di,t} P_{Di,max} \tag{5}$$

$$\forall i,t \qquad z_{Di,t} \in \{0,1\} \tag{6}$$

Equation (3) models the fuel costs $C_{F,t}$ related to the piecewise linearization of the diesel power output P_D,t.Variable $z_{D,t}$ represents the generator state: if it is positive, the diesel operates, otherwise is turned off.

2) Photovoltaic: Photovoltaic energy availability $P_{PVAv,t}$ is an input for the model and it represents the maximum value for the photovoltaic production $P_{PV,t}$. Renewable energy curtailment is allowed only if at least one among battery or inverter constraints is saturated.

$$\forall t \quad (1 - z_{BI,t}) P_{PVAv,t} \le P_{PV,t} \le P_{PVAv,t} \tag{7}$$

If binary variable $z_{BI,t}$ is positive, at least one of inverter or battery constraints is activated, thus leading to the renewable energy curtailment of the exceeding energy.

3) Inverter: Two variables model the total inverter power $P_{inv,t}$, the first to supply power to the grid ($P_{Pinv,t}$) and the second to recharge the storage ($P_{Ninv,t}$). Capability constraints are included as follows.

$$\forall t \qquad P_{inv,t} = P_{Pinv,t} - P_{Ninv,t} \tag{8}$$

$$\forall t \qquad 0 \le P_{Pinv,t} \le z_{C,t} P_{Pinv,max} \tag{9}$$

$$\forall t \quad 0 \le P_{Ninv,t} \le (1 - z_{C,t}) P_{Ninv,max} \tag{10}$$

$$\forall i,t \qquad z_{C,t} \in \{0,1\} \tag{11}$$

The binary variable $z_{C,t}$ ensures that the inverter either supplies the grid or recharges the storage, not simultaneously.

4) Battery: the battery constraints are the maximum and minimum level of energy. The efficiency of the battery η_B and of the inverter η_I are included. In addition, the final storage level must be higher or equal to the initial one ($E_{bat,0}$).

$$\forall t \quad E_{bat,t} = E_{bat,0} - \sum_{\hat{t}=1}^{t} \frac{P_{Pinv,\hat{t}}}{\eta_B \eta_I} + \sum_{\hat{t}=1}^{t} \eta_B \eta_I P_{Pinv,\hat{t}} \tag{12}$$

$$\forall t \qquad E_{bat,min} \le E_{bat,t} \le E_{bat,max} \tag{13}$$

$$\forall t \qquad E_{bat,0} \le E_{bat,t} \tag{14}$$

5) Renewable energy curtailment: The curtailment of the renewable energy is performed when battery constraints or inverter constraints are activated.

$$\forall t \quad z_{I,t} P_{Ninv,max} \le P_{Ninv,t} \tag{15}$$

$$\forall t \quad z_{B,t} E_{bat,max} \le E_{bat,t} \tag{16}$$

$$\forall t \quad z_{BI,t} \le z_{B,t} + z_{I,t} \tag{17}$$

$$\forall t \quad z_{BI,t} \ge z_{B,t} \tag{18}$$

$$\forall t \quad z_{BI,t} \ge z_{I,t} \tag{19}$$

$$\forall i,t \quad z_{B,t}, z_{I,t}, z_{BI,t} \in \{0,1\} \tag{20}$$

Inequalities (15) and (16) allow $z_{I,t}$ and $z_{B,t}$ to be positive only if, respectively, inverter constraints or battery constraints saturate. Inequalities (17)–(20) complete the formulation linking the curtailment enabler variable $z_{BI,t}$ to the saturation observer variables for the battery $z_{B,t}$ and the inverter $z_{I,t}$.

6) Load curtailment: The load curtailment variable $P_{C,t}$ and its cost $C_{C,t}$ are modelled as follow.

$$\forall t \qquad P_{C,t} \ge 0 \tag{21}$$

$$\forall t \quad C_{C,t} = c_{C,t} P_{C,t} \tag{22}$$

7) Maintenance costs: Maintenance costs are included for their share depending on the optimization process, thus the diesel maintenance is assumed to be linear with the diesel working hours.

$$\forall t \quad C_{M,t} = c_{M,t} z_{D,t} \tag{23}$$

8) Load balance: Load demand $P_{L,t}$ is balanced using (24).

$$\forall t \quad P_{D,t} + P_{PV,t} + P_{inv,t} = P_{L,t} - P_{C,t} \tag{24}$$

9) Objective function: The objective function in (25) minimizes the sum of fuel costs, load curtailment, and maintenance costs for a discretized horizon of T periods.

$$\forall t \quad \min \sum_{t=1}^{T} C_{F,t} + C_{C,t} + C_{M,t} \tag{25}$$

B. Stochastic formulation

The proposed stochastic formulation firstly loads from the estimator the forecasted profiles and the probability density functions of both load and renewable energy availability for the following hours. Those data are the inputs to generate a number of Monte Carlo scenarios. Each scenario is optimized evaluating the optimal diesel scheduling through the model described in the previous subsection. When a preset number of scenarios is reached, the Monte Carlo stops and the synthesis process devoted to decision making begins.

Such process determines firstly the diesel unit commitment and lately the exact power level (dispatching).

1) Unit commitment: The proposed UC problem is solved using two major parameters described below. Denoting with $z_{D,t,s}$ the optimum diesel UC for the scenario s and the hour t, we define $p_{D,t}$ as the expected hourly probability of running the generator (EHP) and H_D as the expected number of hours (ENH) the diesel should run in the optimization horizon.

$$\forall t \quad p_{D,t} = \frac{1}{N_s} \sum_{s=1}^{N_s} z_{D,t,s} \tag{26}$$

$$H_D = \sum_{t=1}^{T} p_{D,t} \tag{27}$$

EHP represents the ratio of scenarios per each hour t where the optimal unit commitment of the diesel is the running state, while ENH is the expected numbers of hours the diesel should operate during the optimization horizon. Then, the proposed unit commitment problem is solved as follows:

- We select the number of hours the diesel runs (NHR) in the optimization horizon H_{DC}, by rounding the value of H_D to the closer integer value.
- We select the H_{DC} hours the diesel runs, based on the maximum value of $p_{D,t}$ in the optimization horizon.

Fig. 3 shows an example of the UC decision process; the black bars represent a $p_{D,t}$ plot for a day, while the red bars are the calculated UC. The ENH value for the example is 2.8 hours, thus the NHR value is 3, leading to run the diesel for 3 hours. Then, hours 5, 6 and 20 are chosen because they have the highest value of $p_{D,t}$.

2) Power level decision: For the hours the diesel is committed, its power value $P_{DC,t}$ is calculated as the average value of the diesel power levels for those scenario where the diesel is committed. Denoting with $P_{D,t,s}$ the diesel power level for the scenario s and hour t, $P_{DC,t}$ is calculated as in (28).

$$\forall t \quad P_{DC,t} = \frac{\sum_{s=1}^{N_s} P_{D,t,s}}{\sum_{s=1}^{N_s} z_{D,t,s}} \tag{28}$$

IV. Case Study

The following section describes a numerical case study for the day-ahead operation of a minigrid in Soroti, Uganda. Firstly, we describe the site location of the proposed minigrid. Then, we explain the load data, renewable data, and the minigrid composition used for the simulation. Lastly, we show the simulation results.

A. Input data

The assumptions for the case study are relevant to a possible minigrid in Soroti, Uganda (1.72N 33.6E). The electric grid in Soroti reaches only few buildings, while the rest of the population is nonelectrified or relies on small diesel generators. The minigrid is assumed to supply 100 households with a school and few commercial activities and businesses. The assumptions are supported by surveys [44].

The load profile and uncertainties are calculated with the software LoadProGen 1.0 [45]. The program is based on the stochastic load estimator described in [46] and tested for a college in Bali. The stochastic nature is in parameters of appliances and in two timings of use that increase the variability in the smoothness of the estimated load profile. In our case study we evaluated 200 load profiles using model inputs reported in Appendix E of [44], including a variation of the two timing parameters up to the 30%. The load profile for a typical day is evaluated averaging all the profiles, and we calculated the variance of them. In order to stress the stochastic analysis we considered a doubled variance to model the forecasting errors. A normal distribution for the errors is considered. Fig. 4 shows the load profile and the doubled variance.

According to our review, no hourly irradiance dataset was accessible for Soroti, thus we used the dataset of the closer city Kitale, Kenya, with similar conditions in terms of latitude and climate. The developed estimator model is based on neural network technique. A cloudy day in January is chosen for the case study and Fig. 5 shows the forecasted profile with the variance. A normal distribution models the forecasting errors.

The other parameters of the minigrid are reported in TABLE I. The load curtailment cost is 1 \$/kWh, the fuel cost including

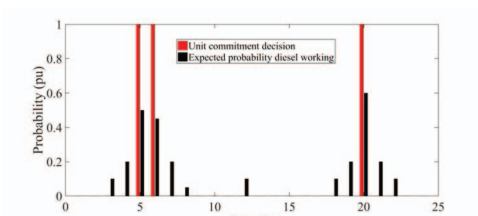

Fig. 3. Example of the unit commitment decision.

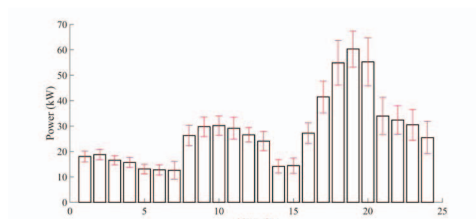

Fig. 4. Forecasted load profile (black) and variance (red).

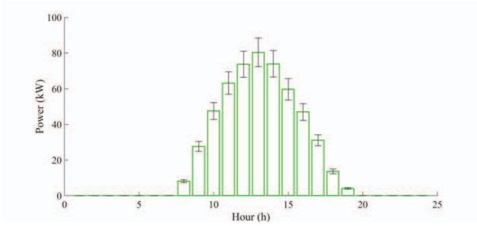

Fig. 5. Forecasted renewable profile (green) and standard deviation (black).

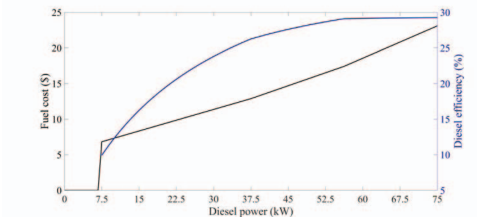

Fig. 6. Piecewise diesel cost and efficiency.

TABLE I
MINIGRID PARAMETERS

Element	CAPEX	Size	Limits *Up*	Limits *Down*	Unit	Efficiency
PV plant	40k$	100	-	0	kW	-
Diesel gen.	25k$	75	75	0	kW	See Fig. 6
Battery inv.	20k$	100	100	-100	kW	95%
Storage	94k$	375	375	75	kWh	96%[1]

[1] Round-trip efficiency

transportation is 1$/l, and the maintenance cost is 0.5 $/h. Fig. 6 shows the total fuel cost and efficiency for the diesel generator.

1400 Monte Carlo scenarios were processed in MATLAB with CPLEX solver.

B. Simulation in case of storage energy initially out of charge

This section is devoted to the simulation of the system, the storage being initially out of charge. Firstly, we use the MILP technique to optimize the diesel and battery operation, deterministically assuming the forecasted load and PV profile; Fig. 7 and Fig. 8 show respectively the correspondent optimal generation dispatching and storage level along the day. Secondly, we apply the stochastic approach of Fig. 2 and we show in Fig. 9, Fig. 10, and Fig. 11 the synthesis of Monte Carlo scenarios.

Fig. 7 shows the deterministic optimal dispatching based on forecasted load and PV profiles. The diesel is committed for hours 1, 2, and 20; in the rest of the day, the renewable energy and the battery meet the load. No load curtailment is required.

Fig. 9 shows the EHP and the computed stochastic commitment. In particular, the value of ENH is close to 3 leading to operate the diesel generator in 3 hours during the day. The unit commitment criterion previously described is applied and hours 1, 2, and 20 are chosen, since corresponding to because those hours correspond to the three highest value of the EHP. Deterministic (Fig. 7) and stochastic (Fig. 9) approaches lead to a different power dispatching of diesel generator, but the

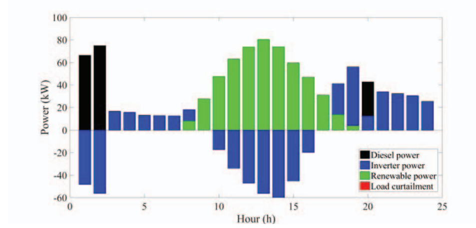

Fig. 7. Generation composition for the deterministic optimization.

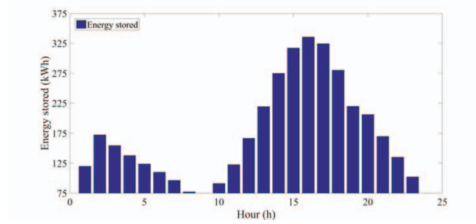

Fig. 8. Battery storage level for the deterministic optimization.

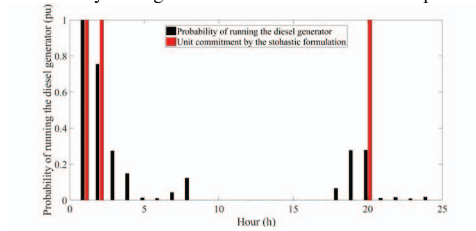

Fig. 9. Probability of running the diesel and proposed unit commitment.

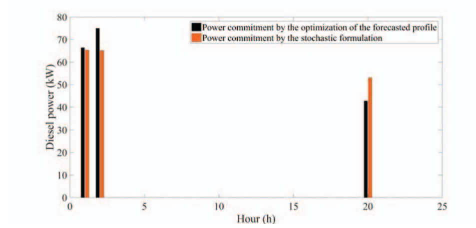

Fig. 10. Power level scheduled.

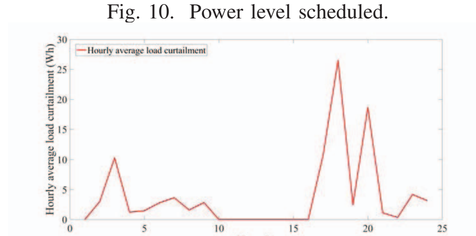

Fig. 11. Hourly average load curtailment by stochastic simulations.

total energy supplied in the two cases is similar (the difference is less than the 0.4%). Conversely, the daily fuel cost of the stochastic formulation (56.9 $/day) is 1.4% lower than for the deterministic optimization based on forecasts (57.7 $/day), due to the non-linearity in the diesel generator.

In addition, the stochastic approach allows the evaluation of the effects of uncertainties on the optimal load curtailment. In specific conditions, load curtailment is more convenient than running the diesel generator at low load. In particular, the MILP optimizer curtails load when this is cheaper than running the diesel generator. In fact, the maximum value of the daily load curtailment costs among the scenarios (6.2 \$) is lower than the costs of running the diesel generator at minimum power as shown in Fig. 6. Even if some scenarios include load curtailment, the daily average load curtailment is low (94 Wh/day), and it mostly occurs during the evening (hours 17 to 21). That information can be an useful tool for the system operator in order to highlight the hours where load curtailment is cost-effective (Fig. 11), thus leading to a better operation. Total costs for the deterministic optimization is 59.2 \$/day, while the average costs for the stochastic one is 59.4 \$/day. The computational time is about 8 min.

C. Simulation with batteries initially half charged

This simulation was carried out to assess the impact of the initial SOC of batteries. Obtained results show that in the deterministic optimization the diesel commitment moves to the evening, as depicted in Fig. 12. The energy stored in the battery, shown in Fig. 13, is enough to supply the load in the night hours until the photovoltaic production is available. Thus, the diesel runs in the hours from 18 to 20 to supply the load, while the battery is discharged later. Supplying a higher share of the load directly from the diesel, instead of charging the battery with the diesel and after discharging the battery to meet the load, leads to higher efficiency, losses of the battery round-trip being avoided. In fact, the fuel costs of the deterministic dispatching (53.5 \$/day) are 7.3% lower than the one in Fig. 7. In addition, running the diesel during the evening is better than during the night, due to noise issues.

The stochastic formulation depicted in Fig. 14 confirms the diesel commitment in the hours from 18 to 20. The ENH is 2.9 h, thus the procedure commits the diesel for the three hours corresponding to the maximum values of ENP, which means hours 18 to 20. Finally, the procedure calculates the power level for each hour and the results are shown in Fig. 13.

Conversely to the diesel operation, the expected load curtailment shown in Fig. 16 moves to the night and morning hours, but the value is still low (55.4 Wh), lower than the one in Fig. 11. The total cost for the deterministic scenario is 55 \$/day, while the average cost for the stochastic optimization is 56.1 \$/day. The computational time is around 7 min.

V. CONCLUSION

The proposed approach has demonstrated the applicability of a stochastic short-term unit commitment and dispatching method based on Monte Carlo simulations to a rural minigrid. Scenarios are optimized singularly and then unit commitment and dispatching are synthesized. The method also evaluates the opportunity and cost-effectiveness of load curtailment. A certain initial storage of the storage can move the diesel to run during the evening hours, thus raising the overall efficiency, reducing noise, pollution, and also the expected load curtailment. We confirm the applicability of MILP technique coupled with Monte Carlo scenarios even in short-term applications with an adequate computational time.

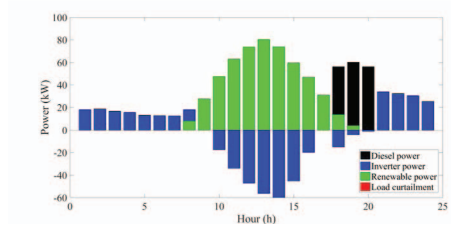

Fig. 12. Generation composition for the deterministic optimization.

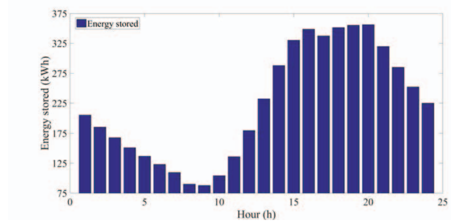

Fig. 13. Battery storage level for the deterministic optimization.

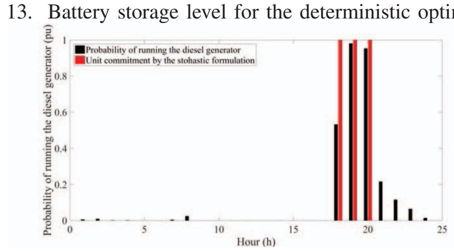

Fig. 14. Probability of running the diesel and proposed unit commitment.

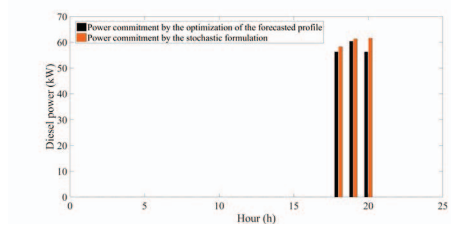

Fig. 15. Power level scheduled.

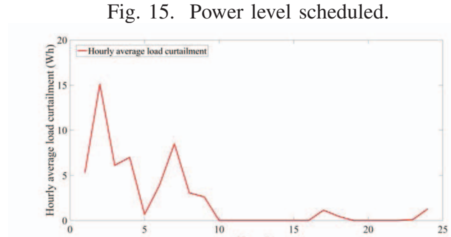

Fig. 16. Hourly average load curtailment by stochastic simulations.

Future investigations will examine different criteria to synthesize results of the Monte Carlo scenarios, even in long-term simulations, in order to improve the savings and robustness of the proposed method. In addition, several load profiles based on real data will be tested and battery degradation costs will be included in order to increase the savings.

Rural minigrids suffer of high fuel price, emissions, and in-site transportation difficulties, and a proper unit commitment and dispatching method improves the quality of supply while reducing the costs.

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