Comparison among deterministic methods to design rural mini-grids: effect of operating strategies

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***Abstract*—Mini-grids are well known to be a suitable solution to foster rural electrification in developing countries, and yet risks and high costs are hampering their spreading. Even though effective tools can help developers to identify the optimal design and operation of a mini-grid, no standard approach have emerged yet. This paper proposes a numerical comparison among deterministic methodologies to optimize a rural mini-grid considering the effect of different operating strategies. The typical load-following and cycle-charging strategies are compared to predictive approaches, as rolling-horizon and a one-shot model, which optimizes both the design and operation together. The two latter models allow achieving additional savings compared to traditional operating strategies, but the computational requirements increase sharply. Results suggest that sizing methodologies using load-following or cycle-charging strategies are more suitable for preliminary design, while predictive approaches should be used for the fine tuning of the size of components. This study can provide guidance on design and operating methodologies for rural mini-grids in developing countries.**

***Index Terms*—isolated hybrid system; microgrids; Mixed integer linear programming; off-grid energy system; optimization**

I. INTRODUCTION

Increasing energy access is a key objective for developing countries [1]. In a world where 1.1 billion people live without electricity and 2.8 billion without adequate cooking facilities, several challenges still have to be overcome, mainly in rural areas [2]. Highlighted as an enabler to foster rural development [3], [4], access to electricity is being promoted by several governments, especially in areas close to the cities [5], but rarely the same approach is appropriate for isolated rural areas of developing countries. In fact, off-grid solutions are often more appropriate in rural areas, because they exploit local sources and prevent the installation of long power grids [6]. In particular, mini-grids that supply several customers through a local power grid can provide a good quality electricity up to Tier 5 (the highest level of access) [5], [7], which enables also the development of commercial and industrial activities.

Typical mini-grids are operated by simple priority-list strategies [8]–[10] that dispatch first the renewable sources, then the energy storage devices, and finally the conventional fuel-fired generators. In the two main approaches, namely the Load-Following (LFS) and Cycle-Charging (CCS) Strategies, the fuel generators are turned on only when the batteries reach their minimum State-Of-Charge (SOC). Their basic difference is that in the LFS the fuel-fired generators only supply the load without recharging the battery, while in the CCS the conventional generators recharge the batteries up to a fixed threshold and are shut down afterwards. As reviewed in [10], [11] and [12], the majority of papers and real mini-grids propose these techniques since they do not require any forecast or expensive control devices. However, recent developments in power electronics have improved the performance and reliability of cheap control devices, so that more advanced techniques could be adopted without requiring expensive or complex control schemes. Several papers highlighted the potential benefits of using predictive approaches also for mini-grids in developing countries [13]–[15]. Authors in [13] developed a fast rolling-horizon tool that performs an optimal re-dispatching procedure of the system every 6 hours, while the real-time balancing of the mini-grid is guaranteed by simple priority-list rules. Conversely, the methodology described in [14] proposes a rolling-horizon approach that re-dispatches the system every 15 minutes by using variable time steps, so to reduce the computational burden. Again, priority rules are used for the very fast real-time balancing.

The optimal design of rural mini-grids is a trendy topic, as proven for instance by [11], [13], [16]–[20]. This topic is strongly related to the one of the operation, since the optimal size of components is typically searched by simulating the technical and economic operation of the mini-grid in different size scenarios. Typical deterministic approaches simulate the future behavior of the mini-grid assuming a given realistic yearly profile of both the demand and renewable production. In this case, classical programming techniques, such as Mixed-Integer Linear Programming (MILP), or heuristic approaches can be used to select the optimal size of components of the mini-grid, with the aim of minimizing the Net Present Cost (NPC) of the system face to such power profiles [11]. In particular, heuristic methods iteratively investigate a number

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of possible size scenarios (also based on the results of the previous iterations) and simulate the operation of each of them. An objective function that accounts for the investment and operating costs is evaluated in every scenario, in order to select the cheapest one. For example, authors in [13] developed a method based on Particle Swarm Optimization (PSO) to identify the optimal sizing of a typical mini-grid, including the design of the tank and the best fuel procurement strategy. To operate the system, a rolling-horizon predictive method was employed, whose outcomes were compared with the results of the classical LFS. The work in [14] describes a similar methodology and results were compared also with CCS. Regarding mathematical optimization techniques, MILP has been widely used in the literature since it provides the global optimum under given mathematical assumptions [21], [22], thus representing the standard approach in power systems for optimizing the system operation [23]. Authors in [24] proposed a MILP methodology to size an isolated energy system serving electricity and thermal loads. However, in order to reduce the computational requirements, the authors approximated the behavior of the system with 12 representative days, rather than with a yearly profile. Conversely, authors in [25] proposed a MILP-based optimization of an isolated system considering the entire year of operation; this increased the computational requirements up to about 3 hours, even though results were within 5% of optimality, as specified in termination criteria. It is important to remark that MILP approaches are limited to piecewise-linear cost functions at best, while methodologies with heuristic solvers can be non-linear, like in [13].

Furthermore, it is worth noticing that any sizing technique, be it based on simulating a LFS, CCS or RHS operating procedure, requires at least the estimation of a typical yearly profile of demand and of renewable production, in order to simulate what the behavior of the mini-grid would be in different size scenarios. In particular, the operation of the mini-grid with LFS and CCS does not require any forecasting activity, while RHS includes a short-term prediction of the demand and renewable production for the hours to come. Therefore, using RHS, also the forecasting activity must be simulated, as in [13]. In this regard, deterministic approaches capture the behavior of the system by means of a single yearly scenario of the demand and renewable production, thus neglecting their uncertainties. Conversely, stochastic approaches consider uncertainties in the design phase by analyzing a number of scenarios whose results are weighted with their probability [13], which increases the robustness of the approach at the cost of higher complexity and computational requirements.

In the present paper, aimed at guiding both developers and researchers, we highlight benefits and drawbacks of deterministic design techniques combined with different operating strategies, assuming that the typical behavior of the system can be approximated with a yearly profile of the demand and of the available renewable production, with a granularity of one hour. Moreover, we propose a novel MILP approach, called One-Shot (OS), able to optimize both the sizing and the operation of the mini-grid assuming the perfect forecasting of load and RES profiles. Additionally, we implemented the methodology described in [13] with the LFS, the CCS and the RHS strategies so to compare them with the OS. In the RHS, the short-term forecasting errors are considered, conversely to what happens in OS. In this preliminary activity, we focused on deterministic approaches so to reduce both the computational requirements and the parameters to analyze. A case study is proposed using consumption data collected from a real mini-grid located in Kenya.

The rest of the paper is organized as follows. Section II describes the mathematical formulation of the OS model, while Section III details the heuristic approaches combined with the LFS, CCS and RHS. Section IV details the case study and Section V reports the results.

II. One-Shot (OS) Model

A. Description

The OS model optimizes both the design and operation of the system by means of MILP, which is very used in power system [22]. In the OS procedure, the solver not only chooses the optimal design of the system but also the best dispatching of components for the entire simulation period, including recharging batteries in advance with respect to real-time needs. The optimization period is the typical year that approximates the multi-year behavior of the system, which is an usual mini-grid with both AC and DC bus composed by a photovoltaic plant, a battery storage, a DC/DC converter, an inverter, and a fuel generator. The objective is minimizing the life-long NPC of the system, which accounts for both investment and operating costs (fuel consumption, maintenance, and the energy-not-served) [13].

B. Mathematical formulation

1) Objective function: The objective function is minimizing the expected NPC detailed in (1), where CAPEX are evaluated through piecewise linear functions of the capacity of each component: the photovoltaic plant, the battery, the DC/DC converter, the inverter, and the fuel generator. Details are reported in equations (2) and (3). The operating costs $OPEX_{s,t}$ of each scenario and time step are averaged according to the Sample Average Approximation method [26]. $OPEX_{s,t}$ relates to the operating costs of the generator $C_{D,O\&M,s,t}$, accounting for both maintenance and fuel expense, and of the load curtailment $C_{LC,s,t}$.

$$\min CAPEX_0 + \sum_{y=1}^{N_T} \frac{\frac{1}{N_s}\sum_{s=1}^{N_s} OPEX_{s,t}}{(1+d)^y} \tag{1}$$

$$\begin{aligned} CAPEX_0 = C_{PV}\left(P_{PV,c}\right) + C_B\left(P_{B,c}\right) + \\ + C_{DCDC}\left(P_{DCDC,c}\right) + C_I\left(P_{I,c}\right) + C_D\left(P_{D,c}\right) \end{aligned} \tag{2}$$

$$C_x\left(P_{x,s}\right) = \text{piecewise linear function (Fig. 2)} \tag{3}$$

$$OPEX_{s,t} = \sum_{t=1}^{N_T=8760} C_{D,O\&M,s,t} + C_{LC,s,t} \tag{4}$$

The operational costs due to the fuel and to the maintenance of the diesel generator are reported in (5). In particular, c_M

is the maintenance cost per unit of the diesel generator rated power, $f_{i,0}$ and $f_{i,1}$ are the intercept and slope of the piece-wise linear cost interval i with respect to the size, $z_{D,s,t}$ is the binary variable that is true when the diesel is in operation and false otherwise, and M_{DC} is a constant large enough so to discard the constraint when the diesel is shut down. $P_{D,c}$ is the optimal design of the diesel generator.

$$C_{D,O\&M,s,t} \geq c_M P_{D,c} + f_{i,0} P_{D,c} + f_{i,1} P_{D,s,t} - (1 - z_{D,s,t}) M_{DC} \tag{5}$$

$$C_{D,O\&M,s,t} \geq 0 \tag{6}$$

The load curtailment costs $C_{LC,s,t}$ are simply related to the corresponding curtailed hourly energy $P_{LC,s,t}$ and to the load curtailment cost c_{LC} per unit of energy loss, as detailed in (7).

$$C_{LC,s,t} = c_{LC} P_{LC,s,t} \tag{7}$$

2) Power balance: The power balances at AC and DC bus are reported in (8) and (9), respectively. $P_{D,s,t}$ is the power supplied by the generator for scenario s and time step t. The inverter dispatching is modeled by $P^+_{I,s,t}$, which is positive when the component supplies power to the AC bus, and by $P^-_{I,s,t}$, which is positive when the component absorbs power from the AC bus. $P_{L,s,t}$ is the load demand and $P_{LC,s,t}$ is the load curtailment. $P_{PV,s,t}$ is the renewable energy exploited and, similarly to the inverter, $P^+_{B,s,t}$ and $P^-_{B,s,t}$ model the power supplied or absorbed by the battery, respectively. The efficiency η_I of the inverter is considered in (9).

$$P_{D,s,t} + P^+_{I,s,t} - P^-_{I,s,t} = P_{L,s,t} - P_{LC,s,t} \tag{8}$$

$$P_{PV,s,t} + P^+_{B,s,t} - P^-_{B,s,t} - \frac{P^+_{I,s,t}}{\eta_I} + P^-_{I,s,t}\eta_I = 0 \tag{9}$$

3) Diesel constraints: Constraint (10) guarantees that the power delivered by the generator is lower than its capacity $P_{D,c}$. Constraint (11) expresses the minimum and maximum power limit of the generator according to whether the generator operates or not, which is modelled with the binary variable $z_{D,s,t}$. The minimum working point of the generator is expressed as a share $\alpha_{Pd,min}$ of its size.

$$0 \leq P_{D,s,t} \leq P_{D,c} \tag{10}$$

$$\alpha_{Pd,min} P_{D,c} - (1 - z_{D,s,t}) M_D \leq P_{D,s,t} \leq z_{D,s,t} M_D \tag{11}$$

4) Battery constraints: Constraints (12) and (13) guarantee that the power exchanged by the battery is lower than the capacity of the battery converter. Constraints (14) and (15) force the battery not to be charged and discharged in the same time step, which is captured by the binary variable $z_{B,s,t}$. Eq. (16) expresses the energy $E_{B,s,t}$ stored in the battery as a function of the energy stored in the battery in the previous time step, the present dispatching of the battery, and the battery efficiency η_B. Constraint (17) specifies the maximum and minimum limit of the energy stored in the battery, as a function of its capacity $E_{B,c}$. Its minimum level is modeled as a share $\alpha_{Eb,min}$ of the capacity of the battery.

$$0 \leq P^+_{B,s,t} \leq P_{B,c} \tag{12}$$

$$0 \leq P^-_{B,s,t} \leq P_{B,c} \tag{13}$$

$$0 \leq P^+_{B,s,t} \leq z_{B,s,t} M_B \tag{14}$$

$$0 \leq P^-_{B,s,t} \leq (1 - z_{B,s,t}) M_B \tag{15}$$

$$E_{B,s,t} = E_{B,s,t-1} + P^-_{B,s,t}\eta_B - \frac{P^+_{B,s,t}}{\eta_B} \tag{16}$$

$$\alpha_{Eb,min} E_{B,c} \leq E_{B,s,t} \leq E_{B,c} \tag{17}$$

5) Inverter constraints: In analogy to the battery, constraints (18) and (19) guarantee that the power exchanged by the inverter is always compliant with the size of the inverter $P_{I,c}$. Equations (20) and (21) guarantee the inverter not to supply and absorb power from the AC bus in the same time, which is set by binary variable $z_{I,s,t}$.

$$0 \leq P^+_{I,s,t} \leq P_{I,c} \tag{18}$$

$$0 \leq P^-_{I,s,t} \leq P_{I,c} \tag{19}$$

$$0 \leq P^+_{I,s,t} \leq z_{I,s,t} M_I \tag{20}$$

$$0 \leq P^-_{I,s,t} \leq (1 - z_{I,s,t}) M_I \tag{21}$$

6) Photovoltaic plant: The power $P_{PV,s,t}$ produced by the PV plant is limited by its size $P_{PV,c}$ and by the available hourly production $P_{PV,Av,s,t}$ of a 1kW-PV plant installed in the same site, as in (22).

$$0 \leq P_{PV,s,t} \leq P_{PV,Av,pu,s,t} P_{PV,c} \tag{22}$$

7) Load curtailment: The load curtailment $P_{LC,s,t}$ must be lower than the load $P_{L,s,t}$ in (23).

$$0 \leq P_{LC,s,t} \leq P_{L,s,t} \tag{23}$$

III. Heuristic-based sizing methodologies (LFS, CCS, RHS)

A. Description

The proposed heuristic methodology is based on a PSO approach that, as shown in Fig. 1, minimizes the NPC of the system accounting for both investment and operating costs, the latter related to fuel, maintenance, and energy-not-served. The load and renewable production, which approximate the multi-year behavior of the system, are first evaluated. Then, the PSO procedure iteratively draws possible size scenarios for the components of the mini-grid, as depicted in the outer loop of Fig. 1. In the inner loop, the procedure then evaluates the OPEX of each of them, by simulating the operation of the system for the entire year, as described in the following section. While authors in [13] simulated only LFS and RHS, in this paper we also consider CCS in order to propose a complete comparison, also including the OS method. Subsequently, the methodology calculates the NPC of the system and when the termination criteria are reached, the procedure stops and the optimal size of the components is assessed.

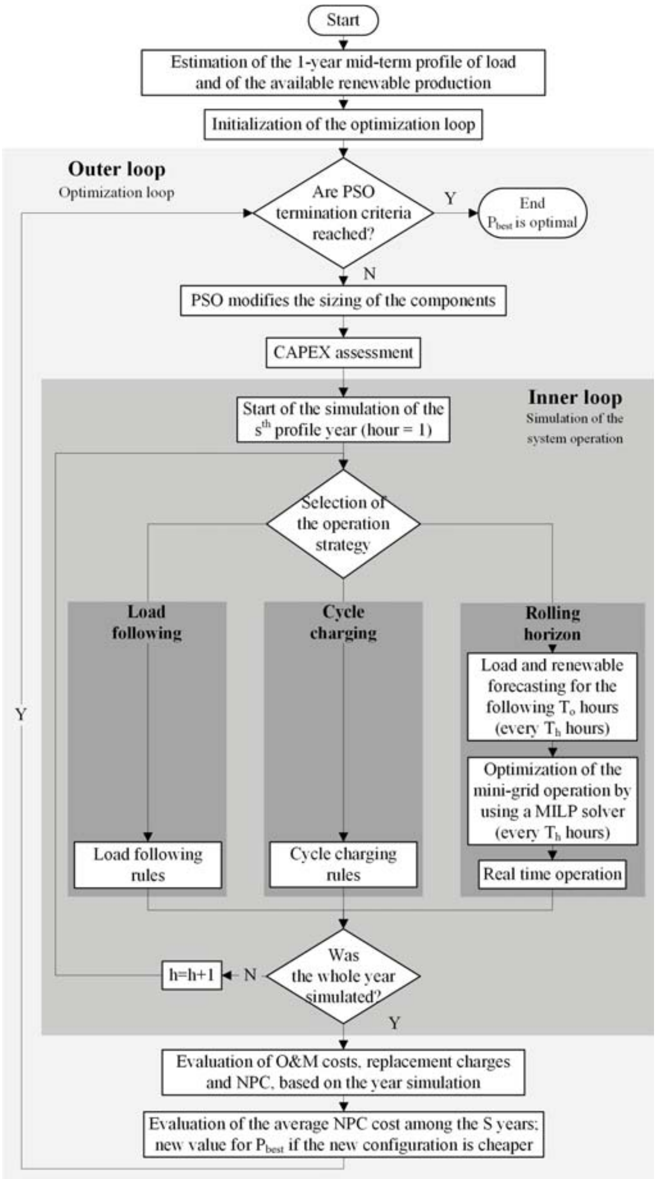


Fig. 1. Algorithm of the proposed heuristic-based optimization.

B. Operating strategies

1) LFS: The Load-Following operating strategy is a merit-order-list method that prioritizes the use of the renewable energy, then the storage system, and finally the fuel generator as a backup source. When batteries reach the minimum SOC, the generator supplies energy only to supply the load, without recharging the battery; otherwise, the generator is kept offline.

2) CCS: Similarly to LFS, also the Cycle-Charging strategy prioritizes renewable energies and storage system as LFS; however, when batteries reach the minimum SOC, the fuel generator is turned on to supply the load and recharge the batteries until they reach a pre-set threshold. This parameter is also optimized in the proposed approach, similarly to the capacity of components. The generator is assumed to supply power at its maximum efficiency (on-off operation). This simplification requires simulating that the generator may be asked to produce only for a fraction of hour, while simulations are performed with hourly resolution.

3) RHS: The rolling-horizon approach is a predictive method that infra-daily redispatches the system to cope with uncertainties of the forecasts, as described in [13]. Every fixed amount of time (i.e. 6h), the power profiles of demand and renewable production of the following 24 hours are estimated. Then, a MILP procedure calculates the corresponding optimal dispatch of the system. The real-time dispatching method based on priority-list rules corrects the previous dispatch due to intrinsic forecasting errors. This approach enables to advance the behavior of the system, thereby the management can achieve additional savings with respect to LFS and CCS. The mathematical formulation is described in [13].

IV. CASE STUDY

A. Description

The comparison of the different sizing methodologies has been tailored to a system of 10000 consumers in the Wajir County, Kenya. While heuristic approaches can optimize the fuel tank including the logistics of the fuel procurement [13], this kind of optimization is not included in the OS due to its complexity and computational requirements. Therefore, the optimized components of the proposed mini-grid are the photovoltaic system, the battery storage, the battery converter, the inverter, and the fuel generator.

B. Demand and available renewable production

The yearly load profile used for the simulations is based on the measurements performed on a close mini-grid for the year 2014. The data originally sampled every 30 minutes were averaged every hour. Hourly Gaussian noise with standard deviation of 20% of the actual demand is introduced to stress uncertainties of the expected demand.

The available renewable production was estimated by using the Graham method [27] tailored with data from the close weather station of Kitale, Kenya.

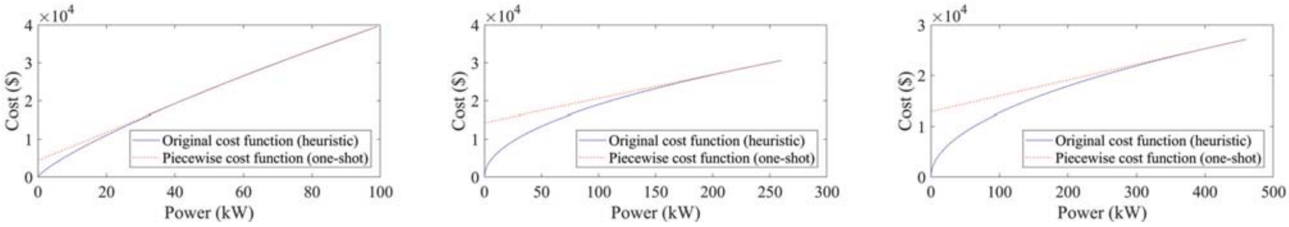
As for RHS, the short-term forecasting error of demand and RES is modeled with a Gaussian function, whose standard deviation varies from 5% to 15% of the expected load, depending on the distance to the real time.

C. Cost parameters and efficiencies

The investment costs of components is described in (24), where x is the component, P_x the corresponding nominal capacity, $C_{0,x}$ is the cost of the component whose size is P_0 and the parameter β_x models the economies of scale.

$$C\left(x\right) = C_{0,x}\left(\frac{P_x}{P_0}\right)^{\beta_x} \tag{24}$$

The costs of PV system and of the batteries are assumed to be proportional to the installed capacity: 800$/kWp and 350$/kWh, respectively. Their maintenance costs are 16$/kWp/y and 3$/kWh/y, respectively. On the other hand,



(a) Generator (b) Inverter (c) Battery converter

Fig. 2. Investment cost function of selected components.

TABLE I
OPTIMAL DESIGN WITH OS AND THE HEURISTIC APPROACHES OPERATED WITH LFS, CCS AND RHS.

Strategy	Exec. time (min)	NPC (k$)	Load curt. (%)	PV (kWp)	Battery (kWh)	Generator (kW)	DCDC Conv. (kW)	Inverter (kW)	$SOC_{CC,end}$ (%)
LFS	1.5	183.3	0.31	743	2069	127	413	247	n.a.
CCS	1.5	181.9	0.47	743	2044	134	419	241	20.6
RHS	274	178.0	0.07	726	2001	59	453	235	n.a.
OS[1]	446	177.4	0.06	716	1990	75	391	236	n.a.

[1]Relative solution tolerance: 5%

the cost functions of the inverter and of the fuel generator are shown in Fig. 2b and Fig. 2a, respectively; the one of the DC-DC converter is the same as of the inverter, but discounted by 33.3% (Fig. 2c). Such pictures show both the non-linear cost function used in heuristic approaches (LFS, CCS and RHS) and the piece-wise linearization for OS. The annual maintenance cost of the converters is 3$/kW/y, while for the generator is 15c$/kW/h for each operating hour. The efficiencies of components are 96% for the battery (roundtrip), 96% for the inverter, and 99% for the DC-DC converter. The efficiency of the diesel increases from around 11% at the minimum operating level (10% of the rated power) up to 33% [13].

The economic value of load curtailment is 1$/kWh and the fuel price is 0.8$/l.

Results were obtained using a 12-core 2.66GHz Xeon computer with 16GB RAM.

V. RESULTS AND DISCUSSION

The optimal designs achieved with the OS and with the three heuristic approaches based on LFS, CCS and RHS are reported in Table I.

It is worth noticing that since OS optimizes both the design and operation together, its global optimum represents theoretically the lowest bound achievable with other operating strategies. In our simulations, due to computational constraints, the solution with OS was achieved with 5% of optimality, but it is still the cheapest one and the priority-list methodologies are more expensive of about 3-4% with respect to the OS method and 2-3% w.r.t. the RHS. LFS and CCS have practically the same objective function, since their difference is lower than 1%. Requiring less than 2 minutes, LFS and CCS outperformed the other solutions in terms of computational requirements. OS was the most time-consuming procedure since it required 7.4h, by far more than RHS (4.5h). Therefore, these results suggest that OS can be used as a reference to compare the objective function achieved under different operating strategies. However, it does not account for uncertainties in the load and renewable production that are considered in the other approaches. Moreover, integrating the optimal sizing of the tank and the fuel logistics into OS is quite challenging due to complexity and computational requirements, contrary to other approaches [13]. Furthermore, although RHS simulates the forecasting errors of both the renewable production and demand, the objective function is still very close to the OS, which means RHS is a promising operating strategy for rural mini-grids.

The optimal design of the photovoltaic plant, the battery and converters is very similar among the methodologies; instead, the one of the generator is halved in the predictive approaches (RHS and OS). In fact, since they analyze in advance the possible behavior of the system, a smaller generator can be used and operated for recharging batteries hours before. Despite that, the total consumption of the diesel increases because the generator supplies more energy, but predictive approaches reduces the specific cost of diesel production including maintenance in respect to LFS. RHS is cheaper than CCS because the former enhances the coordination of components thus leading to lower energy-not-served and less components.

It is also worth noticing that the optimal threshold $SOC_{CC,end}$ to stop recharging the batteries in CCS is roughly the minimum SOC (20%); this means the CCS is collapsing into a LFS and in fact the objective functions are very close.

VI. Conclusion

Aiming to provide guidance on design approaches and operating strategies to researchers, developers and practitioners in the field, this paper presents a detailed comparison of the state-of-art deterministic methodologies to design mini-grid including the effect of operating strategies. The typical sizing methodologies, whose operation is based on priority-list rules, LFS and CCS, were compared to a predictive RHS approach, already discussed in the recent literature, and to a novel One-Shot model. Since OS optimizes the design and operation together, it can reach a global optimum that no other strategy (LFS, CCS, or RHS) can achieve because the future behavior of loads and RES is supposed to be known, however, uncertainties in the short-term forecasts of resources and demand is neglected. Results confirm this consideration but also suggest that RHS is very promising since it is practically as expensive as OS, although it accounts for forecasting uncertainties conversely to OS. In particular, RHS and OS enable a better coordination of components, which allows achieving savings of 2-4% of NPC with respect to LFS and CCS, but the computational requirements of the formers are much higher than LFS and CCS, especially in the OS case. The optimal size of components obtained using the four methodologies is very similar, with the exception of the diesel generator, whose size is roughly halved in RHS and OS due to the predictive capabilities of these methodologies. Therefore, LFS and CCS can be used for the preliminary design with low computational requirements but larger costs, while RHS and OS are more suitable for the refinement stages. Therefore, the design guidelines highlighted in this paper can be used by experts in the field for tailoring the operating strategy and the design methodology of rural mini-grids.

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