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Highlights

Optimal sizing of hybrid PV-diesel-biomass gasification plants for electrification of off-grid communities: An efficient approach based on Benders' decomposition

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- A novel optimal tool for sizing hybrid plants with biomass gasifiers is developed.
- The representative weeks' approach enables efficient data handling.
- Multi-cut Benders' strategy is adopted to deal with extended time horizons.
- Integrating biomass gasifiers in off-grid communities cuts project costs by over 90%.
- Biomass gasification acts as base load power generation to cover most of the local demand.

Optimal sizing of hybrid PV-diesel-biomass gasification plants for electrification of off-grid communities: An efficient approach based on Benders' decomposition

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Abstract

Nowadays, millions of people in remote areas do not enjoy an uninterrupted power supply due to the lack of connectivity to the main power grid. Under such circumstances, the only feasible way to access electricity is typically local power generation, often relying on diesel engine–generator sets or photovoltaic arrays. However, this configuration does not fully exploit local resources such as biomass. Indeed, most isolated areas have access to local biomass production from agricultural activities, which can be used for local electricity generation through gasification. This paper addresses this issue by developing an innovative optimal sizing tool for hybrid power plants integrating biomass gasifiers, specifically designed for isolated areas with access to local biomass production. The novel approach models the particular features of gasification technologies, including long on/off times or restrictive ramping limits. To this end, an efficient methodology based on representative weeks is proposed, which is combined with a solution strategy based on the multi-cut Benders' decomposition, thus resulting in a tractable framework that can deal with a huge amount of data efficiently. One of the most salient features of the new proposal is the consideration of local biomass production, which is included in the methodology through an original algorithm. Thereby, the results obtained take into account that a certain amount of biomass can be obtained locally, thus reaching more accurate and reliable results. The new methodology is applied to a benchmark off-grid community in Ghana. The results demonstrate that the use of gasifiers reduce the project cost notably (by 90%) driven by the reduced cost of biomass, which can be complemented by local production from agricultural activities. In addition, this technology constitutes a clean source of energy, reducing the total CO_2 emissions by 83% compared to the case in which only diesel generators are used. Moreover, it is demonstrated that biomass gasification can effectively act as base load power generation technology to reliably cover most of the local demand, thereby enabling a clean and inexpensive dispatchable local power generation. Finally, a sensitivity analysis demonstrates that the economic feasibility of the plant is more sensitive to the biomass cost than the selling price of biochar, leading to an increment in the total project cost by 33% when the price of biomass increases from 0 to 0.4 \$/kg. Nevertheless, gasification remains as the predominant power generation technology even under unfavorable prices.

Keywords: Biomass gasification, Agricultural waste, Remote electrification, Isolated

communities, Hybrid power plants, Benders' decomposition

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1. Introduction

1.1. Context and motivation

Access to a reliable and uninterrupted electricity supply is a fundamental driver of socio-economic development, influencing various aspects of daily life, from education and healthcare to economic productivity (Williams et al., 2015). However, nowadays a significant portion of the global population, particularly those in remote and off-grid areas, continues to face the challenges of energy poverty. Actually, it is estimated that 13% of the world's population (over 770 million people worldwide) still lack access to electricity (Come Zebra et al., 2021; International Energy Agency (IEA)), with a majority concentrated in sub-Saharan Africa and South Asia (Murshed and Ozturk, 2023; Zhou et al., 2022). Specifically, Sub-Saharan Africa surpasses all other world regions in the number of people living without access to electricity and is also the only region in the world where the number of people living without electricity is increasing (Arranz-Piera et al., 2018; Williams et al., 2015). The consequences of energy poverty are far-reaching, affecting education, healthcare, economic opportunities, and overall quality of life.

In response to this challenge, people living in Sub-Saharan Africa are increasingly benefiting from the rapid development of microgrids (Khodayar, 2017). The generation capacity of these microgrids ranges from kilowatts to megawatts (Khodayar, 2017). From an environmental perspective, microgrids may have lower environmental impacts than traditional systems (Williams et al., 2015). Microgrids are well suited to use local renewable energy resources such as wind, small hydro, solar power, and biomass-based combined heat and power systems (Williams et al., 2015).

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Among Sub-Saharan countries, Ghana is an example of increased investment in rural electrification systems, resulting in a modest improvement in the percentage of the population with access to electricity. Presently, about 28% of the populace living in rural communities lack access to electricity to meet their basic needs in this country (Odoi-Yorke et al., 2022b). However, the Government of Ghana targeted the deployment of 55 renewable energy-based microgrids by 2020, with an ultimate aim of reaching at least 300 microgrids by 2030 (Arranz-Piera et al., 2018). These microgrids are planned to be deployed in lakeside and island communities, as well as rural off-grid communities (Arranz-Piera et al., 2018).

Off-grid areas in Sub-Saharan Africa have traditionally relied on localized power generations solutions, often dominated by diesel engine–generator (DEG) sets or, more recently, solar photovoltaic (PV) arrays (Come Zebra et al., 2021; Khodayar, 2017). While these technologies contribute to electrification of isolated areas (Arranz-Piera et al., 2018), they come with their own specific set of challenges. Diesel generators are often associated with high operational costs, overreliance on imported fuel, and serious environmental concerns due to the emissions of greenhouse gases and other pollutants (Khodayar, 2017). On the other hand, solar PV arrays, albeit being renewable energy sources, face limitations in providing consistent power, especially during nondaylight hours or inclement weather conditions.

The motivation for exploring alternative off-grid electrification solutions appears clear. It involves not only addressing the immediate energy needs of underserved populations in remote areas, but also doing so in an economically feasible and environmentally sustainable way. A compelling option is the deployment of off-grid hybrid power plants, particularly those that integrate photovoltaic (PV) technology, biomass gasification and diesel generators. Biomass gasification, in particular, holds significant potential for the electrification of remote rural communities where access to local biomass production is available (Sansaniwal et al., 2017). Indeed, many isolated areas in African countries have abundant biomass resources from agroindustrial activities, which can be used for decentralized electricity generation through gasification processes (Anvari et al., 2023; Arranz-Piera et al., 2018; Ramamurthi et al., 2016; Salisu et al., 2021; Sánchez-Lozano et al., 2023). Unlike traditional power generation technologies from biomass, gasification allows for a more efficient utilization of local resources and can contribute to a cleaner and more sustainable energy mix. Accordingly, the research presented in this paper focuses on the optimal sizing of hybrid PV-diesel-biomass gasification plants for electrification in off-grid communities. The emphasis is on developing an efficient approach based on Benders' decomposition, considering the unique characteristics of gasification technologies. The methodology integrates representative weeks, offering a practical framework capable of handling substantial datasets effectively.

1.2. Literature review

A review of the existing literature has revealed that rural electrification remains a significant challenge in Sub-Saharan countries such as Ghana, where a substantial part of the population still lacks reliable access to electricity. To date, most research initiatives have focused on integrating renewable energy sources, with little attention given to the utilization of bioenergy. For example, Arranz-Piera et al. (2018) investigated the feasibility of decentralized electrification through agricultural waste gasification in rural Ghana. After examining five communities, the research revealed a favorable match between projected electricity demand and potential energy generation from agricultural residues. Korzhenevych and Owusu (2021) examined the lack of knowledge about households' willingness to pay for renewable-based electricity in Ghana, particularly for rural electrification. The paper concluded by discussing policy considerations for tariff regulations and business models in implementing renewable minigrids for rural electrification beyond the national grid. Odoi-Yorke et al. (2022a) assessed the techno-economic feasibility of a PV/biogas/battery hybrid minigrid system to provide reliable and cost-effective electricity for remote communities in Ghana. Despite a higher initial investment, the hybrid system has the lowest levelized cost of electricity (LCOE), making it both economically favorable and environmentally friendly. In a different work, Odoi-Yorke and Woenagnon (2021) suggested the implementation of a hybrid solar photovoltaic/fuel cell system to power a remote telecommunications base station in Ghana. This suggested hybrid system allowed reaching an LCOE of 0.222 USD/kWh, leading to a saving of 43–67 tonnes of CO_2 per year. Ansong et al. (2017) presented a hybrid system to supply electric power to an off-grid mining company in Ghana. The system comprises solar photovoltaic energy, fuel cells, batteries, and a diesel generator. The electricity production of the system amounts to 152.99 GWh, with an energy cost (LCOE) of $0.22–0.25/kWh. Sackey et al. (2023) proposed the development of a microgrid to provide electricity in a grid-connected system for a Zipline facility in Sefwi–Wiawso, Ghana. This system includes solar panels, Li-ion batteries and a diesel generator. The economic feasibility assessment resulted in a nominal discounted payback period of 2.11 years. Afonaa-Mensah et al. (2024) assessed the impact of agro-processing productive loads on the performance of a hybrid solar PV/diesel system for rural electrification in Ghana. The results suggest that incorporating productive use loads into the community's overall demand enhances the load factor and correlation between solar power and load in rural areas. This enhanced load profile decreases the LCOE, making solar PV/diesel hybrid renewable energy system more appealing. Finally, Agyekum and Nutakor (2020) examined the techno-economic viability of hybrid power plants integrating PV–Wind–Diesel generator–Battery and Wind–Diesel generator–Battery systems in southern Ghana. The results for the LCOE for the PV-Wind-DG-Battery system were $0.382/kWh and $0.396/kWh, respectively.

On the other hand, regarding the integration of biomass gasification in hybrid renewable energy systems, Ribó-Pérez et al. (2021) addressed the challenges surrounding biomass gasifiers' integration into microgrid simulation tools, particularly in HOMER. They introduced a procedure to simulate electric generation from syngas in downdraft biomass gasification plants using HOMER, demonstrating the technical and economic viability of islanded biomass-photovoltaic hybrid microgrids compared to grid extension alternatives through successful case studies in remote Honduran and Zambian communities. Montuori et al. (2014) used HOMER to optimize the microgrid of a hybrid system composed of a diesel generator, a natural gas genset and a biomass gasification plant. In another study by Rajbongshi et al. (2017), HOMER was used to optimize a grid-connected system in rural Nepal, specifically in Jhawani village, using PV, biomass gasification and a diesel generator.

To leverage the benefits of different energy sources, electrification of isolated areas is normally enabled through combining different generation technologies. In this regard, renewable-based technologies (e.g. solar or wind) are combined with so-called dispatchable units such as DEGs in order to ensure electricity supplying in the presence of little availability of the renewable source. In this way, hybrid power plants for rural electrification become more complex and, in order for them to be operated efficiently, optimal coordination of the different assets becomes an essential element of these kinds of installations. In this context, energy management tools are increasingly gaining importance in recent dates. Huge research efforts have been made in the field of energy management in microgrids, contemplating different approaches such as uncertainty modeling (Tostado-Véliz et al., 2022b), reliability (Tostado-Véliz et al., 2022a) or cooperation among multiple systems (Ali et al., 2023).

However, the research regarding optimal energy management in microgrids involving biomass units is scarce. In particular, Zheng et al. (2018) proposed a demand-side management strategy for optimal energy management of a biomass-based microgrid under uncertainty, encompassing electrical and thermal loads. Wang et al. (2016) developed a multi-layer energy management methodology, in which different time scales are addressed in order to efficiently determine operating signals for a biomass-DEG-wind system encompassing energy storage. Zhou et al. (2019) presented a model of predictive control for isolated microgrids involving biomass units and energy storage. Nevertheless, this work did not seek for the optimal operational point of the different units and rather focus on real-time control to ensure power balance. Singh and Basak (2021) studied the viability of a PV-biomass hybrid power plant under a typical Indian scenario, demonstrating that the resulting levelized cost of energy is acceptable and therefore the proposed system plant feasible economically.

The references above, however, focus on already-installed systems and do not handle with the optimal planning of hybrid power plants involving biomass units. In this regard, there are only a few works which cope with the design of biomass units for electrification of isolated areas. For instance, Ribó-Pérez et al. (2021) proposed a gasifier model for the software HOMER, which can be used for planning purposes. However, HOMER does not optimally design the plant and relies on heuristic control rules, which do not ensure the optimality of the solution and do not properly model the particularities of gasifiers such as slow dynamics. Gamil et al. (2021) compared different sizing strategies using a metaheuristic solver to determine the best sizing solution for an isolated microgrid involving biomass generators. However, this reference again recurs to heuristic-based solution approaches, which eventually do not ensure the optimality of the solution and, frequently, entail unaffordable computational costs. Lastly, Prakash and Dhal (2022) incurred in the same issues of previous references, as the software HOMER is used for designing standalone systems consisting of biomass and diesel-based generators combined with renewable assets.

1.3. Research gaps

On the basis of the review above, it can be concluded that there is still a lack in optimal planning tools for isolated microgrids incorporating gasifiers, and therefore, proper analytical models for gasifiers need to be developed and studied. In this regard, a Mixed-Integer-Linear Programming (MILP) framework for optimal sizing of biomass units in isolated areas was proposed by V. and Verma (2021). This methodology effectively ensures the optimality of the solution, since analytical solvers are used. However, the developed model for diesel and biomass units are quite simple and do not faithfully reflect the operational characteristics of such technologies. For instance, ramping and minimum on/off times were not modeled. Thereby, the results obtained with this methodology, although eventually minimize the total cost of the project, are undoubtedly overoptimistic due to the inaccuracy of the model.

Moreover, V. and Verma (2021) did not discuss possible strategies to alleviate the computational cost of the resulting optimization framework. Note that planning tools typically need to handle with a large amount of data that might be evaluated over a long-time period (e.g. 25–30 years). In this sense, V. and Verma (2021) simply declare variables for each day over a year basis instead of considering different scenarios and long-term degradation/inflation of components. This complexity may represent a challenge for conventional machines and solvers. Moreover, long-term degradation/inflation rates are not accommodated in a simple an intuitive way.

Finally, seasonal local biomass production is not properly contemplated by V. and Verma (2021). It is noteworthy that in agricultural communities, biomass is locally accessible and it should be considered in the planification process, accounting for a free biomass production that may be eventually leveraged for clean electric power generation.

1.4. Contributions

This work is motivated in the gaps commented above. In particular, the main contributions of the present work are listed below:

- Developing a proper model for biomass gasifiers, taking into account slow dynamics and duty on/off times of this technology. It represents a novelty itself compared to V. and Verma (2021), where such features were not considered and therefore more accurate results are expected to be achieved with the developed model.

- The developed gasifier model is integrated into a properly designed MILP model for optimal planning of hybrid power plants for isolated communities integrating PV, gasification and diesel units. One of the salient features of the developed model is its ability to easily include long-term degradation/inflation rates that capture long-time variation of some input parameters (e.g. degradation of PV panels).

- Unlike V. and Verma (2021), local biomass production and storage is included in the model and solution strategy through a developed approach. Thereby, such asset is properly quantified and its impact on final results can be evaluated. It should be noted that ignoring local biomass production may lead to pessimistic results where the importance of gasification is diminished.

- Instead of considering all the days in a year as input parameters (e.g. solar irradiance), an approach based on representative weeks is considered in this paper, capable of capturing slow dynamics as well as minimum on/off times of gasifiers. This approach allows reducing the number of inputs and therefore minimizing the computational burden of the problem while its accuracy is preserved. To this end, a clustering technique based on the k-medoids method is employed.

- In contrast to V. and Verma (2021), a solution strategy based on decomposition techniques is proposed, in order to alleviate the intrinsic computational burden of the planning framework. The application of a multi-cut Benders strategy decomposes the planning model into years and representative weeks, which can be solved in a decoupled fashion resulting in an affordable approach that can be managed by average machines.

The developed tool is tested on a real rural community in Ghana and the results are discussed and commented, thus validating the developed optimization framework as well as the techno-economic viability of gasifiers in isolated rural communities is further demonstrated.

In the remainder of this paper, Section 2 describes the research background. Section 3 presents the developed mathematical models for the proposed planning tool, including a reliable MILP model for gasifiers. Section 4 proposes a solution strategy based on the Benders' decomposition, which eventually alleviates the computational cost of the proposed framework. Section 5 presents a case study with results, while Section 6 concludes the paper.

2. Preliminaries

2.1. Overview of the gasification technology

To overcome the limitations associated with diesel generators and photovoltaic (PV) technology, the integration of energy from biomass or bioenergy as an additional energy source may be considered. Among the different biomass conversion technologies, biomass gasification processes stand out as an attractive choice for power generation due to their versatility, efficiency, and environmental benefits (Erdiwansyah et al., 2023). Gasification is a thermochemical process in which a carbonaceous solid feedstock, such as biomass, is partially oxidized and converted into a combustible gas mixture. This process allows most of the energy content of the solid fuel to be transferred to the gas phase, leaving a minor fraction as a carbonaceous solid residue known as biochar, which is discharged as a by-product.

In the particular case of air-blown biomass gasification, the resulting lean gas mixture is referred to as producer gas, which primarily consists of hydrogen (H_2), carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), nitrogen (N_2), water vapor (H_2O), and smaller fractions of other light hydrocarbons (Aguado et al., 2023; Hagos et al., 2014). The biomass introduced into the gasifier undergoes partial oxidation in an autothermal process, wherein the exothermic combustion reactions supply sufficient heat to sustain the endothermic gasification reactions necessary for the formation of producer gas (Basu, 2018).

The producer gas from biomass gasification is a versatile fuel for decentralized power generation using internal combustion engines, gas turbines, external heat engines or even fuel cells (Basu, 2018; Martínez et al., 2012). However, internal combustion engines coupled to electric generators currently stand out as the most common choice for small-scale biomass gasification plants (< 1 MW). This preference is attributed to their numerous advantages over alternative power generation units, including affordable capital investment, modularity, reliability, reasonably high operating efficiency and satisfactory part-load performance (Basu, 2018; Hagos et al., 2014).

In contrast to other thermochemical biomass conversion technologies such as pyrolysis or hydrothermal carbonization, the main product of gasification is the gaseous fuel, rather the solid by-product (Hornung et al., 2021). However, gasification biochars exhibit a higher degree of carbonization and are more porous than pyrolysis biochars, especially those produced at higher temperatures (Fryda and Visser, 2015). Thus, despite its lower yield, biochar from gasification is recognized as a valuable by-product for carbon sequestration and soil amendment (Hansen et al., 2015). The yield of biochar from biomass gasification in fixed-bed gasifiers is approximately a linear function of the biomass consumption (Dogru et al., 2002; Mazhkoo et al., 2021), typically ranging between 5–15% by weight (Aguado et al., 2023, 2021; Allesina et al., 2018; Dogru et al., 2002; Mazhkoo et al., 2021). This potentially marketable by-product opens numerous opportunities for new business models.

2.2. Microgrid under study

In the broader context of off-grid electrification initiatives aimed at addressing the energy disparities in rural areas across Sub-Saharan Africa, it is pertinent to examine the case of Ghana. In 2015, approximately 15% of the Ghanaian population, equivalent to an estimated 4 million people residing in sparsely populated rural communities, lacked access to electricity (Kemausuor and Ackom, 2017). Projections indicated that these communities were expected to remain unconnected by 2020 (Kemausuor and Ackom, 2017). The country's electricity sector encounters multiple challenges, including frequent blackouts (Seglah et al., 2023). On the other hand, there are areas of Ghana where access to the electricity grid is non-existent (Macrotrends Ghana). The recurring power outages and limited grid accessibility have resulted in the over-reliance on diesel-powered generators in both residential and industrial areas, which poses significant environmental challenges (Seglah et al., 2023).

With a 21% share of the country's gross domestic product (GDP) (Seglah et al., 2023), the agricultural sector in Ghana witnesses the dispersion of crop residues throughout the country. These residues are primarily utilized for traditional purposes and often burned in the fields, leading to health and environmental concerns. However, recognizing the bioenergy potential of these residues, there is an opportunity to utilize them for power generation through the biomass gasification technology, thereby facilitating the electrification of off-grid communities.

In addressing the electrification needs of an isolated rural community in Ghana, a microgrid is proposed as a solution. As illustrated in Fig. 1, the microgrid under study comprises three primary energy sources: a solar PV array, a diesel engine–generator set, and a biomass gasification plant. The use of battery energy storage is avoided, due to the detrimental effects of high operating temperature in tropical or equatorial regions (Sowe et al., 2022), leading to significant degradation issues. Indeed, tropical and subtropical environments, characterized by intense solar radiation, a relative humidity range of 70% to 80%, and year-round average temperatures between 25 °C and 31 °C, pose considerable challenges on battery performance (Martiny and Jossen, 2011). Moreover, electricity consumption primarily occurs in the evening, relying heavily on diesel generators or batteries exceeding their service life (Adu-Poku et al., 2023). In addition, grid-extension option is not a viable solution for rural areas due to the high cost of extending the grid for very low population density and dispersed houses (Arranz-Piera et al., 2018; Come Zebra et al., 2021). As a consequence, real-time demand balancing is paramount, requiring dynamic adjustment of energy generation to match ever-changing demand levels. The diesel generator function as a back-up power source, capable of handling unexpected peaks in demand. Optimizing the efficiency of the gasifier and diesel generator is essential in the absence of energy storage. This allows for agile responses to varying loads while upholding overall system efficiency. Additionally, load management protocols may be necessary when demand surpasses supply to maintain grid stability.

2.3. Data characterization

Planning problems commonly span for long-term periods (more than 10 years), representing the typical lifetime of some equipment. In this particular problem, the expected lifetime of PV panels is about 30 years (Mohamed et al., 2022). Under these premises, optimal planning tools have to manage a huge amount of data. For instance, if one considers a project lifetime of 25 years, with 1-hour time resolution (typical settings in many electrical planning tools (Moreira et al., 2021)), each decision variable will have a size of 30×8760, which becomes unaffordable for average machines and conventional optimization solvers.

This complexity motivates the use of data reduction techniques. These approaches explode the repetitive features of typical datasets in electric and energy-related tools (demand, PV potential,

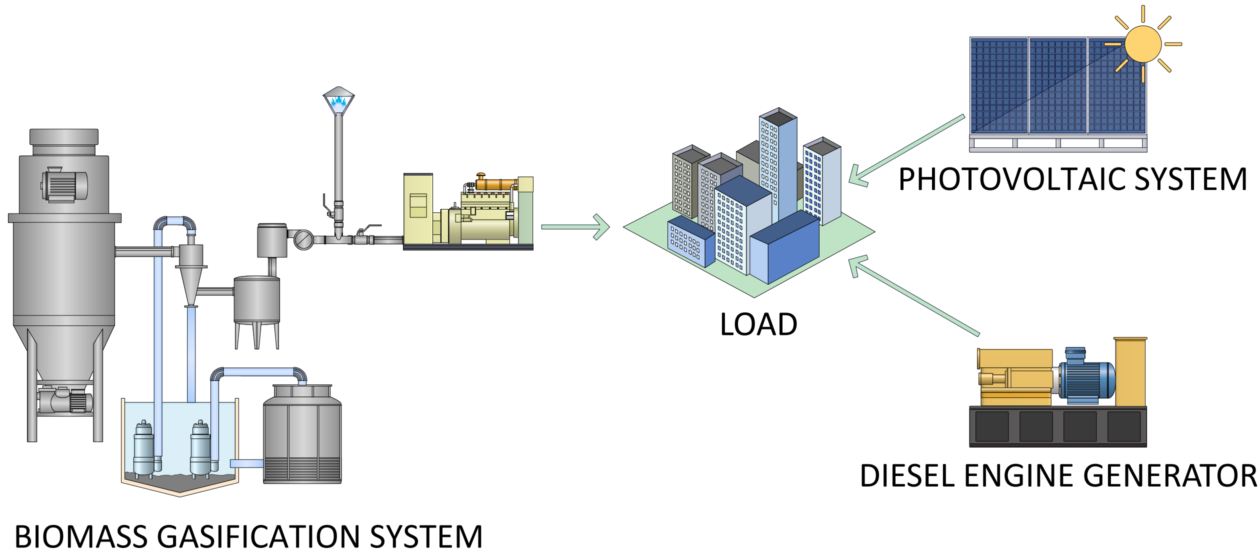

Figure 1: Simplified schematic diagram of the microgrid under study.

etc), to represent the entire dataset by just a reduced number of representative members. This technique is commonly known as "representative days", and has been used in a number of references (Sangadiev et al., 2022). This way, the size of the original dataset can be notably reduced without compromising the reliability of results, thus making the problem tractable in practice.

In this particular problem, representing the entire dataset by representative weeks instead of days is a more suitable option. The reason for this adoption is that gasifiers have large thermal inertia (Aguado et al., 2023), and normally require long on/off time periods (Fusselman et al., 2006; Moock and Trapp, 2000), which cannot be faithfully represented over a daily time horizon. In this regard, it is assumed that measures regarding local demand and PV potential are available for a year and can be considered as inputs of the problem. Then, the k-medoids clustering method is used for reducing the original dataset into a minimum set of representative weeks. The k-medoids is a mature clustering technique that normally offers good results (Pinto et al., 2020). Its idea is based on the traveler problem, through which it gathers the original raw data into clusters, which are eventually represented by a unique member called medoid (the representative weeks in this study).

The main drawback of the k-medoids is the necessity of specifying the number of medoids *a priori*. Note that the number of medoids (i.e. representative weeks) should be high enough to represent the original dataset properly, but not excessively high to entail a computational challenge. In this paper, the total number of medoids was selected using the elbow method (Tostado-Véliz et al., 2023a), which seeks for a trade-off between robustness and efficiency.

3. Mathematical models

In the following sections, the mathematical formulation corresponding to the optimal planning of the MG under consideration is presented. Note that it is assumed that the project horizon spans for $|\mathcal{Y}|$ years, each one represented by $|\mathcal{R}|$ representative weeks.

3.1. Project cost

The total project cost can be defined, as follows:

$$C = \mathrm{CAP} + \sum_{y \in \mathcal{Y}} \left\{ \rho_y \left(REP_y + OM \right) + \sum_{r \in \mathcal{R}} |\Omega_r| \, E_{yr} \right\} \tag{1}$$

where

$$\rho_y = (1+s)^{y-1} \tag{2}$$

The first term in Eq. (1) represents the capital costs in which the project incurs once over the entire lifetime. They account for the installation costs of the different units, which are frequently a function of the installed power, as follows:

$$\mathrm{CAP} = \sum_{x} K^x \overline{p}^x ; x \in \{PV, DEG, G\} \tag{3}$$

Note that capital costs corresponding to PV panels include the installation costs of the inverter. Then, Eq. (1) includes some yearly costs that are evaluated once each year and updated according to the interest rate. Firstly, the replacement costs are evaluated as:

$$\mathrm{REP}_y = \sum_x r_y^x \Upsilon^x \overline{p}^x ; x \in \{PV, DEG, G\} \tag{4}$$

Note that replacement costs are similar to capital costs, but only evaluated when the y^{th} of the vector r_y^x is equal to 1, which indicates that the x^{th} element needs to be replaced at the y^{th} year. On the other hand, operation and maintenance costs are also accounted yearly and considered a function of the total capital costs (Mohamed et al., 2022), as follows:

$$\mathrm{OM} = \sum_x K^x o^x \overline{p}^x ; x \in \{PV, DEG, G\} \tag{5}$$

Lastly, the last term in Eq. (1) includes the weekly costs, which include different expenditures that are evaluated each representative week, as follows:

$$E_{yr} = F_{yr}^B + \Delta\tau \sum_{t \in \mathcal{T}} \left\{ F_{yrt}^{DEG} + F_{yrt}^{NS} + F_{yrt}^{SD} - F_{yrt}^{Bio} \right\} \tag{6}$$

It is worth commenting that weekly costs are multiplied in Eq. (1) by the number of weeks in a year that are actually characterized by the r^{th} representative week (i.e., $|\Omega_r|$). This way, weekly costs are evaluated over a year basis and can be compared with the rest of terms in Eq. (1).

The first term in Eq. (6) accounts for the biomass that it is purchased the r^{th} representative week at the y^{th} year, as said Eq. (7). Note that it is assumed that the community under study produces a certain amount of biomass yearly, which is not actually accounted for in Eq. (7), as explained in Section 3.4.

$$F_{yr}^B = B_{yr} \pi_1^B \left[1 + \varphi^B (y - 1) \right] ; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{7}$$

It is worth noting that biomass cost is assumed to be impacted by long term inflation rates (i.e. φ^B), this way, long-term variation in prices are properly reflected in the project cost. The second term in Eq. (6) accounts for the diesel cost, which is a quadratic function of the energy generated (Tostado-Véliz et al., 2023b), as follows:

$$F_{yrt}^{DEG} = a_y^F u_{yrt}^{DEG} + b_y^F p_{yrt}^{DEG} + c_y^F \left(p_{yrt}^{DEG}\right)^2 ; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{8}$$

Note that coefficients in Eq. (8) are the well-known fuel-cost coefficients, which are subjected to long-term inflation due to growth prices. This long-term variation is included in the developed formulation, as follows:

$$x_y^F = x_1^F \left[1 + \varphi^F (y - 1)\right] ; \forall y \in \mathcal{Y} \wedge x \in \{a, b, c\} \tag{9}$$

In order to keep the optimization model linear and tractable by off-the-shelf solvers, quadratic terms in Eq. (8) can be linearized using piecewise representations (see Appendix A). The third term in Eq. (6) corresponds to the costs due to non-served energy. In the developed tool, in order to discard solutions that may incur in excessive non-served energy, they are penalized, as follows:

$$F_{yrt}^{NS} = p_{yrt}^{NS} \xi ; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \tag{10}$$

The fourth term in Eq. (6) represents the start-up and shutdown costs of the gasifier, which are given in Eq. (11). Lastly, the fifth term in Eq. (6) represents the incomes by the sale of biochar, which is obtained as a by-product of the gasification process. It is considered that the biochar produced in commercial gasification plants is a linear function of the biomass consumption, as indicated in Eq. (12) (Dogru et al., 2002). Note that it is also assumed that the biochar cost is impacted by long-term inflation rates.

$$F_{yrt}^{SD} = \varrho^{G,S/D}\left(on_{yrt}^{G} + off_{yrt}^{G}\right); \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{11}$$

$$F_{yrt}^{Bio} = w^{B} p_{yrt}^{G} \pi_{1}^{Bio}\left[1 + \varphi^{Bio}(y-1)\right]; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{12}$$

It is worth noting that start-up and shutdown costs for the DEG were not included, as these kinds of costs are typically significant in thermal units, while DEG is an internal combustion technology (Tostado-Véliz et al., 2022a).

3.2. Project-level constraints

It is reasonable to assume that capital costs cannot be higher than a pre-established initial budget, as defined by Eq. (13).

$$\mathrm{CAP} \leq \Pi \tag{13}$$

3.3. Operational constraints

The following constraints aim at properly modeling the different components in the MG under study, capturing their different features. Firstly, the following power balance must be ensured any time instant.

$$p_{yrt}^{DEG} + p_{yrt}^{G} + p_{yrt}^{PV} + p_{yrt}^{NS} = p_{yrt}^{Dis} + p_{1rt}^{D}\left[1 + \varphi^{D}(y-1)\right]; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{14}$$

Note that Eq. (14) includes non-served and dissipated energy. In particular, non-served energy is penalized in the objective function and therefore expected to be minimum if the penalty cost (i.e., ξ) is sufficiently large. In Eq. (14), long-term variation of the local demand is considered, which is a reasonable assumption, given that local demand can grow significantly throughout the project lifetime. In order to keep the model coherent, non-served and dissipated powers must be positive, as given by Eq. (15).

$$p_{yrt}^{x} \geq 0; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{NS, Dis\} \tag{15}$$

Power generated by gasifiers and DEGs should lie within given bounds, as indicated in Eq. (16), where binary constraints are included to represent the commitment status of each unit, so that they can be disconnected for convenience.

$$u_{yrt}^{x} \underline{p}^{x} \leq p_{yrt}^{x} \leq u_{yrt}^{x} \overline{p}^{x}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{DEG, G\} \tag{16}$$

By contrast, PV generation is in fact limited by the instantaneous PV potential, which is a function of weather parameters (i.e. solar irradiance and ambient temperature). In this paper, PV potential is considered an input of the problem that can be represented by means of representative weeks. Under these premises, Eq. (17) reflects the maximum deliverable PV power, accounting for yearly degradation of PV panels.

$$p_{yrt}^{PV} \leq \overline{p}^{PV} \left[1 - \varphi^{PV} (y - 1)\right] \vartheta_{rt}^{PV}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{17}$$

Ramp constraints for DEGs and gasifiers are represented in Eq. (18), limiting the variable power between consecutive time slots, and thus reflecting the inertia of these technologies. On the other hand, Eqs. (19)–(22) model the logic coherency of on/off status of the gasifier and DEG units.

$$p^x_{yrt-1} - R^x \leq p^x_{yrt} \leq p^x_{yrt-1} + R^x; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \backslash t = 1 \wedge x \in \{DEG, G\} \tag{18}$$

$$u^x_{yrt} - u^x_{yrt-1} = on^x_{yrt} - off^x_{yrt}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \backslash t = 1 \wedge x \in \{DEG, G\} \tag{19}$$

$$u^x_{ini} - u^x_{yr1} = on^x_{yr1} - off^x_{yr1}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge x \in \{DEG, G\} \tag{20}$$

$$u^x_{yrt=1} = u^x_{yrt=|\mathcal{T}|}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge x \in \{DEG, G\} \tag{21}$$

$$u^x_{yrt}, on^x_{yrt}, off^x_{yrt} \in \{0, 1\}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{DEG, G\} \tag{22}$$

Finally, Eqs. (23)–(27) model the minimum start-up and shutdown time limits of the gasifier and DEG (Constante-Flores and Conejo, 2023). It is noteworthy that the same constraints are applied to both the gasifier and DEG, despite that the diesel generator can be considered a fast-acting unit. Nevertheless, the aim is to present a generic mathematical modeling easily adaptable to different sizes and layouts. This way, if the DEG is considered as a flexible source, constraints Eqs. (23)–(27) can be simply ignored for this unit.

$$\sum_{i=t}^{t+T^{x,U}-1} u^x_{yri} \geq on^x_{yrt} T^{x,U}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \left\{1, \ldots, |\mathcal{T}| - T^{x,U} + 1\right\} \wedge x \in \{DEG, G\} \tag{23}$$

$$\sum_{i=t}^{|\mathcal{T}|} \left\{u^x_{yri} - on^x_{yrt}\right\} \geq 0; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \left\{|\mathcal{T}| - T^{x,U} + 2, \ldots, |\mathcal{T}|\right\} \wedge x \in \{DEG, G\} \tag{24}$$

$$\sum_{i=t}^{t+T^{x,D}-1} \left\{1 - u^x_{yri}\right\} \geq off^x_{yrt} T^{x,D}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \left\{1, \ldots, |\mathcal{T}| - T^{x,D} + 1\right\} \wedge x \in \{DEG, G\} \tag{25}$$

$$\sum_{i=t}^{|\mathcal{T}|} \left\{1 - u^x_{yri} - off^x_{yrt}\right\} \geq 0; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge t \in \left\{|\mathcal{T}| - T^{x,D} + 2, \ldots, |\mathcal{T}|\right\} \wedge x \in \{DEG, G\} \tag{26}$$

$$\sum_{t=1}^{T^{x,U}} \left\{1 - u^x_{yrt}\right\} = 0; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge x \in \{DEG, G\} \tag{27}$$

3.4. Modeling local biomass production and storage

It is considered that the community can leverage biomass produced locally from agriculture activities, which can be locally stored and used in the gasification plant without cost, thus obtaining and local resource for electricity generation. However, local biomass production and storage is a year-basis variable that cannot be easily evaluated in the week-basis model above. As an example, let us assume that the estimation of the total locally produced biomass per year is feasible and is denoted as $\overline{W}_y^B$. One could simply include a variable in the model limiting the amount of weekly biomass consumption by $\overline{W}_y^B$. However, this model simply enforces that, at each representative week, the biomass consumed in gasification is not higher than the annual production, which is not coherent and does not ensure that the annual consumption of biomass is not higher than the actual biomass collected. Another alternative is simply dividing $\overline{W}_y^B$ by the number of weeks in a year. However, this option broadly assigns a fixed amount of biomass to each week, without considering the particularities of each scenario (demand, PV potential, etc.).

To address the aforementioned issues, a dummy weekly biomass limit, denoted as W_{yr}^B, is introduced. The calculation of this limit follows a procedure involving five steps, as outlined below:

1. Solve the planning problem without including biomass limit.

2. Obtain the optimal gasifier generation per hour, representative week and year (i.e. $p_{yrt}^{G,*}$).

3. Estimate the following weekly energy ratio as

$$\Phi_{yr}^G = \frac{|\Omega_r| \sum_{t\in\mathcal{T}} \Delta\tau p_{yrt}^{G,*}}{\sum_{r\in\mathcal{R}} |\Omega_r| \sum_{t\in\mathcal{T}} \Delta\tau p_{yrt}^{G,*}}; \forall y \in \mathcal{Y} \land r \in \mathcal{R} \tag{28}$$

4. Calculate W_{yr}^B as

$$W_{yr}^B = \frac{\Phi_{yr}^G}{|\Omega_r|} \overline{W}_y^B; \forall y \in \mathcal{Y} \land r \in \mathcal{R} \tag{29}$$

5. Include the following constraint in the problem

$$B_{yr} \geq \Delta\tau w^B \sum_{t\in\mathcal{T}} p^G_{yrt} - W^B_{yr}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{30}$$

The procedure above presents two main advantages. On the one hand, the biomass consumption cap is coherently assigned to each week according to the optimal gasifier usage, which is obtained after running the proposed problem relaxing the biomass consumption limit (step 1). On the other hand, the model incorporates the option of externally purchasing biomass, as indicated in Eq. (30). Thereby, the acquired biomass can be employed for gasification and thus the use of this technology is not limited by the local biomass production.

4. Proposed solution strategy

4.1. Motivation

To properly justify the solution strategy adopted, the developed planning problem is expressed in a compact form as follows:

$$\min_{\overline{\boldsymbol{p}},\boldsymbol{\Xi}_{yr},\boldsymbol{u}_{yr}} f\left(\overline{\boldsymbol{p}}\right) + \sum_{y\in\mathcal{Y}} \sum_{r\in\mathcal{R}} |\Omega_r|\, E_{yr}\left(\boldsymbol{\Xi}_{yr}, \boldsymbol{u}_{yr}\right) \tag{31a}$$

subject to:

$$\mathrm{CAP} \leq \Pi \tag{31b}$$

$$\boldsymbol{h}\left(\boldsymbol{\Xi}_{yr}, \boldsymbol{u}_{yr}\right) = \boldsymbol{b}_{yr}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{31c}$$

$$\boldsymbol{g}\left(\boldsymbol{\Xi}_{yr}, \boldsymbol{u}_{yr}\right) \leq \boldsymbol{d}_{yr}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{31d}$$

$$\boldsymbol{q}\left(\boldsymbol{\Xi}_{yr}, \boldsymbol{u}_{yr}\right) \leq \overline{\boldsymbol{p}}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{31e}$$

$$\boldsymbol{u}_{yr} \in \{0, 1\}; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{31f}$$

where $f = \text{CAP} + \sum_{y \in \mathcal{Y}} \rho_y \left(\text{REP}_y + \text{OM}\right)$ and the sets of decision variables are $\overline{\boldsymbol{p}} = \left\{\overline{p}^{PV}, \overline{p}^{DEG}, \overline{p}^{G}\right\}$, $\boldsymbol{\Xi}_{yr} = \left\{p_{yrt}^{DEG}, p_{yrt}^{G}, p_{yrt}^{PV}, p_{yrt}^{NS}, p_{yrt}^{Dis}, B_{yr}\right\}$ and $\boldsymbol{u}_{yr} = \left\{u_{yrt}^{DEG}, on_{yrt}^{DEG}, off_{yrt}^{DEG}, u_{yrt}^{G}, on_{yrt}^{G}, off_{yrt}^{G}\right\}$.

In Eq. (31), the objective (31a) represents the capital, yearly and weekly costs defined in Eqs. (3)–(12), whereas (31b) is the project constraint (13). On the other hand, (31c) and (31d) are the equality and inequality operational constraints, respectively. However, the limit constraints (16) and (17) are included in (31e) for convenience of the notation. Finally, (31f) defines binary variables as in (22).

The framework (31) effectively solves the considered planning problem and yields optimal values for the variables $\overline{\boldsymbol{p}}$. Nonetheless, its resolution becomes challenging if the sizes of $\mathcal{Y}$ and $\mathcal{T}$ are large, as commonly in planning tools.

To ease the resolution of Eqs. (31) and make the planning problem tractable in practice, its decomposable structure is exploded. Indeed, the objective function (31a) is clearly decomposable into the terms f and E, which are in turn a function of the variables $\overline{\boldsymbol{p}}$ and $\left\{\boldsymbol{\Xi}_{yr} \cup \boldsymbol{u}_{yr}\right\}$, thus advocating for the use of decomposition techniques.

Decomposition methods have been widely employed to alleviate the computational cost of large-scale optimization problems (Conejo et al., 2006). Among the different techniques available, the Benders' decomposition is one of the most popular. In this paper, the application of Benders' decomposition to the framework (31) is undertaken, as detailed in the following sections.

4.2. Sub-problems

The Benders' decomposition identifies complicated variables and constraints. In (31), it is easily observed that $\overline{\boldsymbol{p}}$ and (31e) represent the complicated variables and constraints, respectively. Applying the Benders' decomposition to (31) involves splitting the original framework into a master problem and a number of sub-problems (one per year and representative week). In particular, the sub-problems for the m^{th} iteration pertaining to the Benders' algorithm read as:

$$\boldsymbol{u}_{yr}^{(m),*} \in \underset{\boldsymbol{\Xi}_{yr}^{(m)},\boldsymbol{u}_{yr}^{(m)}}{\text{argmin}} E_{yr}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m)}\right) \tag{32a}$$

subject to:

$$\boldsymbol{h}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m)}\right) = \boldsymbol{b}_{yr} \tag{32b}$$

$$\boldsymbol{g}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m)}\right) \leq \boldsymbol{d}_{yr} \tag{32c}$$

$$\boldsymbol{q}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m)}\right) \leq \overline{\boldsymbol{p}}^{(m)} \tag{32d}$$

$$\boldsymbol{u}_{yr}^{(m)} \in \{0, 1\} \tag{32e}$$

As seen, (32) is actually the weekly operational problem, assuming that complicating variables are fixed. Actually, (32) is a MILP from which sensitivities with respect to complicating variables cannot be accurately derived. To overcome this issue, and following the idea in (Kazempour and Conejo, 2012), the linear version of (32) given in (33) is solved, in which binary variables are assumed to be equal to their optimal values obtained from (32).

$$\mu_{yr}^{(m)} \in \min_{\hat{\boldsymbol{p}},\boldsymbol{\Xi}_{yr}^{(m)}} E_{yr}\left(\boldsymbol{\Xi}_{yrn}^{(m)}, \boldsymbol{u}_{yr}^{(m),*}\right) \tag{33a}$$

subject to:

$$\boldsymbol{h}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m),*}\right) = \boldsymbol{b}_{yr} \tag{33b}$$

$$\boldsymbol{g}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m),*}\right) \leq \boldsymbol{d}_{yr} \tag{33c}$$

$$\boldsymbol{q}\left(\boldsymbol{\Xi}_{yr}^{(m)}, \boldsymbol{u}_{yr}^{(m),*}\right) \leq \hat{\boldsymbol{p}} \tag{33d}$$

$$\hat{\boldsymbol{p}} = \overline{\boldsymbol{p}}^{(m)} : \ \mu_{yr}^{(m)} \tag{33e}$$

4.3. Master problem

In a Benders' fashion, the master problem can be written, as follows:

$$\min_{\overline{\boldsymbol{p}}^{(m)},\alpha^{(m)}_{yr}} f\left(\overline{\boldsymbol{p}}^{(m)}\right)+\sum_{y\in\mathcal{Y}}\sum_{r\in\mathcal{R}}\alpha^{(m)}_{yr} \tag{34a}$$

Subject to:

$$CAP \leq \Pi \tag{34b}$$

$$\alpha^{(0)}_{yr} \geq 0; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \tag{34c}$$

$$\overline{\boldsymbol{p}}^{(0)} \geq 1 \tag{34d}$$

$$\alpha^{(m)}_{yr} \geq |\Omega_r| \left[E_{yr}\left(\boldsymbol{\Xi}^{(v)}_{yr}, \boldsymbol{u}^{(v)}_{yr}\right) - \mu^{(v)}_{yr}\left(\overline{\boldsymbol{p}}^{(m)} - \overline{\boldsymbol{p}}^{(v)}\right)^{\intercal}\right]; \forall y \in \mathcal{Y} \wedge r \in \mathcal{R} \wedge v \in \{1, 2, \ldots, m-1\} \tag{34e}$$

where (34) is the objective function of the planning problem but, instead of including the weekly costs explicitly, they are modeled by the auxiliary variable α. This variable is approximated by cuts coming from the subproblems given in (34e), where sensitivities with respect to complicating variables are included. On the other hand, (34b) is the project constraint (13), while (34c)–(34d) include an initial lower bound for α and the complicating variables, respectively, in order to fast up the convergence. It is worth noting that (34) corresponds to the multi-cut variant of the original Benders' decomposition (Kazempour and Conejo, 2012), as a total of $|\mathcal{Y}| \times |\mathcal{R}| \times (m-1)$ cuts are incorporated each iteration.

4.4. The algorithm

The 1–7 step procedure below is designed to solve the model (31) in a multi-cut Benders' fashion.

1: Initialize $UB = \infty$, $LB = -\infty$ and $m = 0$.

2: If $m = 0$, solve (34) without (34e). Otherwise, solve (34) without (34c)–(34d).

3: Obtain $\overline{\boldsymbol{p}}^{(m)}$ and update $LB = \sum_{y\in\mathcal{Y}}\sum_{r\in\mathcal{R}}|\Omega_r|\,\alpha^{(m)}_{yr}$

4: Solve each sub-problem (33) and obtain $\boldsymbol{u}^{(m),*}_{yr}$; $\forall y \in \mathcal{Y} \wedge r \in \mathcal{R}$.

5: Solve each linear sub-problem (34) and derive sensitivities $\mu^{(m)}_{yr}$; $\forall y \in \mathcal{Y} \wedge r \in \mathcal{R}$.

6: Update $UB = \sum_{y\in\mathcal{Y}} \sum_{r\in\mathcal{R}} |\Omega_r|\, E_{yr}\left(\boldsymbol{\Xi}^{(m)}_{yrn}, \boldsymbol{u}^{(m),*}_{yr}\right)$ and check convergence as

$$\frac{UB - LB}{UB} \leq \varepsilon \tag{35}$$

where $\varepsilon = 0.01$ in this paper.

7: If the algorithm converges, stop. Otherwise, $m = m + 1$ and go to step 2.

It is worth noting that the algorithm above must be executed twice to obtain the final solution. Indeed, this procedure is firstly run to obtain W^B_{yr} following the procedure given in Section 3.4, and a second time to obtain the final solution including the constraint (30).

4.5. Limitations

From the operational point of view, the model developed in this paper presents few limitations. Indeed, gasification and DEG units are modeled with sufficient detail for planning purposes. Operational statuses of both units have been well-characterized by commitment statuses, and their intrinsic limitations have been modeled through ramping limits and minimum start-up and shut-down times.

Therefore, the main shortcoming of the new proposal may reside in the characterization of data based on representative profiles. In this regard, this approach has to be considered to keep the model tractable in practice. In consequence, some demand and PV potential profiles in the database are not included in the analysis and they are instead represented by a representative member. On the basis of the authors' experience and preliminary experiments, this fact does not significantly affect the final results, and therefore, the developed methodology can be considered reliable. However, careful selection of the input profiles is recommended. In this sense, the proposed methodology based on k-medoids clustering reveals to be reliable and its use is straightforward.

5. Case study

In this section, a case study is presented along with results in order to validate the developed tool and analyze the results obtained.

5.1. Case description

Ghana presents an ideal case for the implementation of a microgrid due to several compelling factors. Firstly, the country experiences frequent challenges in its power supply infrastructure, leading to intermittent or lack of electricity access, particularly in remote and off-grid areas, which are often underserved or disconnected from the main grid. Secondly, Ghana boasts abundant renewable energy resources, including solar and biomass, which can be efficiently harnessed within the framework of a microgrid, thereby contributing to both environmental preservation and energy security. The cost-effectiveness of microgrid solutions incorporating solar photovoltaic and biomass gasification systems, especially when considering the reduction in transmission losses associated with decentralized energy generation, represents a financially prudent choice.

With an annual provision of 100 tonnes of agricultural biomass waste, the gasification plant is assumed to operate with a specific consumption rate of 1.3 kg of biomass per kWh of electricity (Aguado et al., 2023). In addition, the assumed biochar production rate is 15% by weight of the biomass consumption (Aguado et al., 2023, 2021). The electricity generated in gasification plants exhibits a linear relationship with the consumption of biomass. This linear relationship also extends to the production of biochar, where the quantity of biochar generated is directly correlated with the amount of biomass used in the process.

The gasifier operates most efficiently when running at its maximum load capacity, but it requires at least a third of this capacity to function reliably at its minimum operational threshold. Biomass gasifiers have both a slow response time and a long startup period because of the large thermal mass involved (Reed and Das, 1988). Thus, it is assumed that the gasifier requires approximately 3 hours to transition from a cold state to reach steady-state operation and initiate electricity production, but can take longer if the biomass gasification unit has been down for a long time (Moock and Trapp, 2000). Moreover, once the gasifier is shut down, the system is assumed to require a 72-hour idle period before it can be restarted. Simultaneously, the diesel generator acts as a backup to compensate for energy production shortfalls during gasifier downtime, in cases of sudden load increases or during hours when there is no solar production. Management of these energy sources is required to address the challenges posed by the gasifier's operational limits to maintain an uninterrupted and reliable power supply within this off-grid microgrid system.

5.2. Input data

The developed mathematical models and solution strategy were coded under Matlab R2021a and solved using Gurobi (Gurobi Optimization L.L.C., 2021). All the simulations were run on an Intel® Core™ i7-10700 K with 32.00 GB RAM, taking 1-h time resolution.

The developed planning tool takes representative weeks as inputs in order to represent the local demand and PV potential over a year basis. For this purpose, the methodology described in Section 2.3 was applied to the PV potential estimated in Ghana at 2020 from (Commission), while the local demand was taken from a local community in the same country, scaling up to 250 kW of yearly peak power. As result, the original yearly set of data was reduced to seven representative profiles, which are plotted in Fig. 2. As observed, the resulting representative space presents notable seasonal variability in both demand and PV potential, being in consequence characterizable through representative weeks.

In the formulation of the mathematical model, various assumptions have been considered, the most relevant of which are outlined below:

- A 30-year project lifetime is considered, aligning with the typical warranted lifetime of PV panels (Mohamed et al., 2022).

- The investment cost of the gasification technology, including the gasifier, producer gas conditioning unit, and engine–generator set, is conservatively estimated at approximately

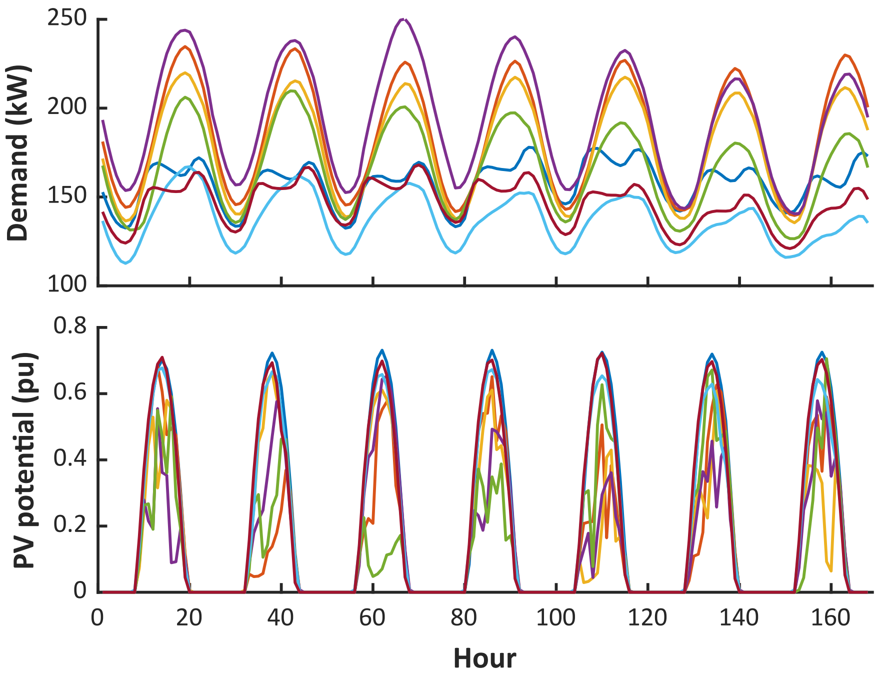

Figure 2: Representative weeks used in the simulations. Local demand (*top*) and PV potential (*bottom*).

$3000/kW on a commercial scale (Sánchez-Lozano et al., 2023). For comparison, Salisu et al. (2021) reported $2580/kW for an off-grid gasification CHP plant in Nigeria.

- The yearly local biomass production was estimated at 100 tonnes, and any excess biomass requirement needs to be procured. Feedstock costs may be reasonable in cases where agricultural residues can be collected and transported over short distances. However, feedstock costs can escalate when substantial transport distances are necessary due to the lower energy density of biomass, as observed in the trade of wood chips and pellets. According to a report by the IRENA (International Renewable Energy Agency (IRENA), 2012), feedstock costs vary from $10 per tonne for low-cost residues to $160 per tonne for internationally traded pellets. Hence, for the purposes of this paper, a pragmatic assumption was made, setting the cost of purchased biomass at $100 per tonne.

- The biochar obtained as by-product can be sold, which represents an additional income. The price of biochar exhibits significant variability, as a result of the wide variation in its physical and chemical characteristics (Campbell et al., 2018). Reported prices of this by-product typically range from $80 to over $13,000 per tonne (Campbell et al., 2018). However, given the absence of a consolidated market in Sub-Saharan Africa, its price was conservatively estimated at around $50 per tonne.

- The reported average operation and maintenance cost for a few selected biomass gasification plants is 10.4% of total capital expenditure (Alves et al., 2021). This paper also provides a conservative estimate for the maintenance cost of the gasification technology, which has been assumed to be 15% of the total capital investment.

- Biomass gasification plants for electric power generation exhibit significant chemical and thermal inertia, leading to difficulties in accommodating sudden load changes (Lanagran et al., 2023). As a result, the gasifier's dynamic operation cannot handle large fluctuations in their power output, as the producer gas must comply with specific quality standards. Accordingly, it should be noted that a maximum ramping rate of 30% per hour has been assumed in this paper.

- The cost of non-served energy was taken equal to $2000/kWh and the interest rate equal to 1.5 %/year (Arévalo et al., 2021).

The rest of economic and technical parameters are based on different references and reported in Tables 1–3. As observed, the DEG is considered as a flexible fast-acting unit, for which the constraints (18)-(27) can be omitted, whereas the gasifier presents limited dynamic response, with long start-up and shutdown times and slow power ramping features (Moock and Trapp, 2000). Finally, long-term inflation and degradation rates are reported in Table 4.

In order to properly analyze the results obtained and further validate the developed tool, different cases are examined. In particular, Case A explores only the installation of DEG, while Case

Table 1: DEG data used in the simulations.

Parameter	Value	Ref.
Capital cost	\$500/kW	Afonaa-Mensah et al. (2024); Tostado-Véliz et al. (2021)
Replacement cost	\$400/kW	Tostado-Véliz et al. (2021)
Maintenance cost	5% of the total capital cost	Tostado-Véliz et al. (2021)
Fuel coeff.	\$0.6/h, \$0.05/kWh, \$0.02/kWh^2	Tostado-Véliz et al. (2023b)
Lifetime	15 years	Montuori et al. (2014); Tostado-Véliz et al. (2021)
Minimum power	10 % of rated power	Tostado-Véliz et al. (2021)
Minimum start-up time	0 hours	Tostado-Véliz et al. (2023b)
Minimum shutdown time	0 hours	Tostado-Véliz et al. (2023b)
Ramping rate	100% of rated power per hour	Tostado-Véliz et al. (2023b)

Table 2: Gasifier data used in the simulations.

Parameter	Value	Ref.
Capital cost	\$3000/kW	Salisu et al. (2021); Sánchez-Lozano et al. (2023)
Replacement cost	\$2000/kW	Salisu et al. (2021); Sánchez-Lozano et al. (2023)
Maintenance cost	15% of the total capital cost	Alves et al. (2021)
Start-up cost	\$250	Estimated
Lifetime	15 years	Sánchez-Lozano et al. (2023)
Biomass consumption	1.3 kg/kWh	Aguado et al. (2023)
Biochar production	0.15 kg/kg of biomass	Aguado et al. (2023)
Minimum power	30 % of rated power	Aguado et al. (2023)
Minimum start-up time	3 hours	Moock and Trapp (2000)
Minimum shutdown time	72 hours	Fusselman et al. (2006)
Ramping rate	30% of rated power per hour	Lanagran et al. (2023)

Table 3: PV panels data used in the simulations.

Parameter	Value	Ref.
Capital cost	\$1200/kW$_p$ + \$100/kW$_p$ (inverter)	Afonaa-Mensah et al. (2024); Konneh et al. (2023)
Replacement cost	\$100/kW$_p$ (inverter)	Mohamed et al. (2022)
Maintenance cost	1% of the total capital cost	Mohamed et al. (2022)
Lifetime	30 years	Mohamed et al. (2022)

B combines DEG with PV. Finally, Case C considers the installation of the different generation technologies, namely DEG, PV and gasifier.

5.3. *Planning results*

Initially, the focus is on the sizing results obtained in the three studied cases for different available budgets, as shown in Fig. 3. It can be observed that, as the available budget increases,

Table 4: Long-term variation of plant parameters.

Parameter	**Value**
Degradation of PV panels	0.5 %/year
Fuel cost inflation	2 %/year
Biomass cost inflation	0.5 %/year
Biochar cost inflation	0.5 %/year
Load growth	0.1 %/year

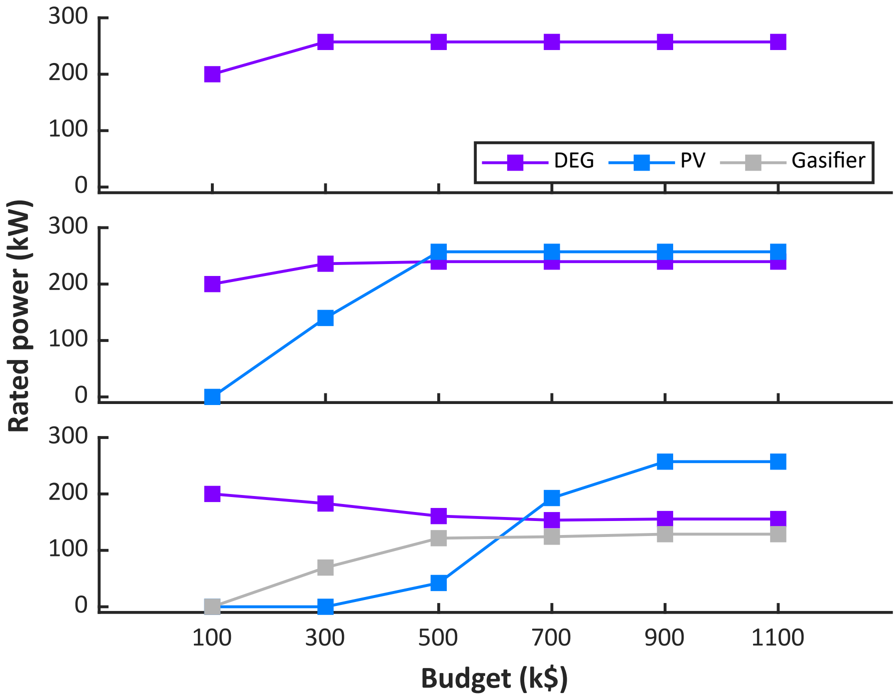

Figure 3: Sizing results for different available budgets in Case A (top), Case B (middle) and Case C (bottom).

more DEG capacity can be installed. However, there is a cap at 257.25 kW beyond which the project cost cannot be improved. Note that this power value corresponds to the peak power at the end of the project lifetime, taking into account the load growth rate. Therefore, the developed tool coherently designs the DEG to meet the peak demand in the community and, as expected, the total project cost cannot be further reduced without considering other generation technologies.

In contrast, PV panels can complement the diesel generator in Case B. In fact, the PV installed power is higher than the resulting rated power for DEG for budgets higher than $300k. It indicates that the developed tool firstly prioritizes installing DEG in order to fully cover the local demand

and thus avoiding non-served energy. Once the local demand can be fully satisfied and there is available budget yet, PV panels are installed in order to obtain a local renewable generation that eventually allows reducing the total project cost.

Lastly, it is interesting to note that considering the biomass gasification technology in Case C allows reducing the size of the DEG below 200 kW. This is because the gasification system can act as dispatchable power unit and is only limited by their slow dynamic response. In such a case, the developed planning tool considers the minimum DEG rated power to cover the local demand attending to dynamic restrictions, whereas the gasifier serves as a base load generator. This is clearly seen for low budgets (~\$100k), when the planning tool only installs DEG thus prioritizing to fully satisfy the local demand. As in Case B, the PV panels complements the other technologies by providing an inexpensive generation technology.

5.4. Energy analysis

In this section, the focus is on the energy balance throughout the project lifetime, which is shown in Fig. 4. As expected, generation through DEG is similar for different budgets in Case A, since it is the unique technology available. However, the installation of PV panels allows reducing the energy generated by DEG by approximately 26% in Case B. This effect is more remarkable in Case C due to the installation of gasifiers. Actually, the energy generated through DEG can be further reduced by 83% due to the combined action of gasifiers and PV arrays.

It is worth noting that, in Case C, the biomass gasifier becomes the most used technology, accounting for nearly 78% of the total energy generated. This demonstrates that biomass gasification is an attractive generation technology, especially due to the presence local biomass production that eventually enables a free generation technology (without considering capital, maintenance and replacement costs). Actually, as illustrated in Fig. 5, the estimated biomass purchased throughout the project lifetime grows with the available budget below Π = 500 k\$ and decreases slightly beyond this value. This outcome highlights several interesting remarks:

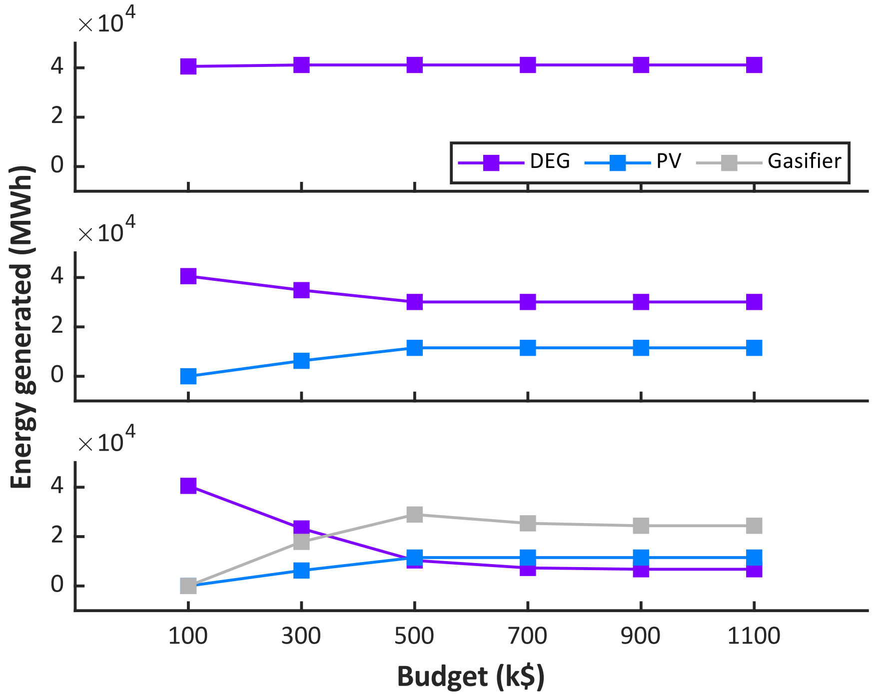

Figure 4: Energy generation by different technologies throughout the project lifetime for different available budgets in Case A (*top*), Case B (*middle*) and Case C (*bottom*).

- Electricity generation through biomass gasification is clearly more attractive than DEGs. This is due to the fuel cost in each case. Thus, while gasifiers can be supplied at minimum cost leveraging local biomass production, the diesel cost is notably higher. Even when biomass has to be purchased externally, this option is preferred rather than diesel due to the low cost of biomass.

- Although electricity generation through biomass gasification is relatively inexpensive, PV production is still preferred, as expected. This explains why power generation using biomass gasifiers decreases when $\Pi > 500$ k$. Indeed, beyond this value, the PV capacity reaches its maximum (see Fig. 3), and therefore, the power generated through biomass gasification can be reduced.

- Even with high PV capacity, biomass gasification is the dominant technology due to its full availability, whereas PV potential is limited to the central hours of the day.

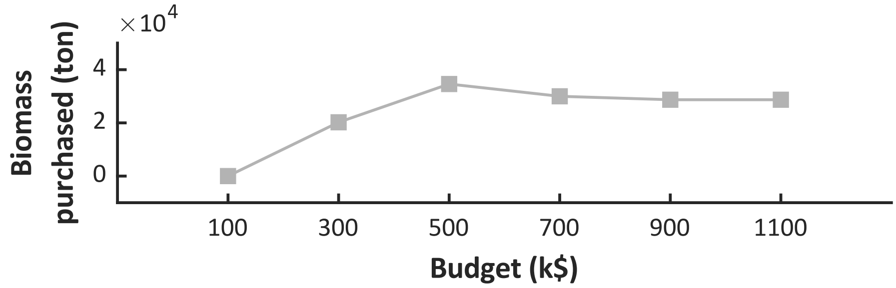

Figure 5: Total biomass purchased throughout the project lifetime.

5.5. *Reliability analysis*

In this section, the total non-served and dissipated energy is analyzed. As observed in Fig. 6, when the installed DEG power is very low, non-served energy grows dramatically. This is because, at low budgets, the DEG is not able to fully supply the total demand (note that the installed DEG in this case is 250 kW, while the peak power is above 250 kW). By contrast, when the biomass gasifier is not installed, the energy dissipated is low. This is due to the flexibility of PV and DEG, which enable real-time adjustments in delivered power. However, the gasifier presents limited dynamic response, forcing to dissipate energy in some periods to absorb ramping or lower bound power constraints.

Furthermore, the aim of this section is to analyze the reliability of each technology (DEG, PV, and gasification) individually. To this end, three cases are studied in Fig. 7 considering the installation of only one generation technology and Π = 1100 k$. In this table, the amount of non-served energy is analyzed in each case. As observed, PV undoubtedly results in the less reliable technology due to the limited availability of PV potential. In this regard, gasification is clearly more reliable, being able to provide a continuous supply and reducing the non-served energy by 63% compared with PV. However, the results in Fig. 7 reveal that DEG is more reliable in term of power supply, being able to fully supply the local demand. This is because gasifiers are even restricted for their ramping and on/off duty constraints. In this sense, DEG is considered a more flexible technology, being able to easily adapt its operation to demand variations.

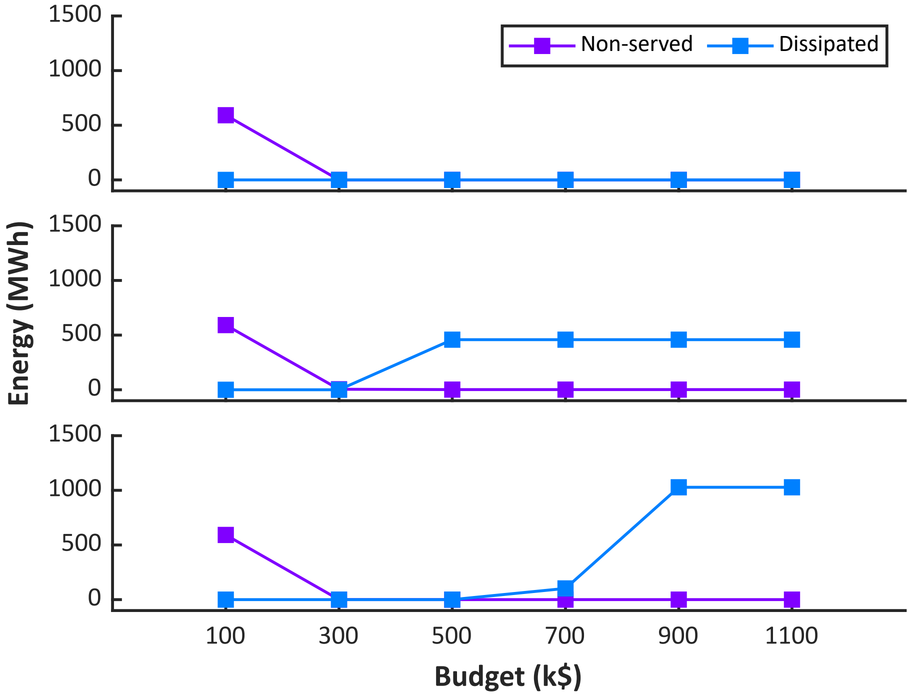

Figure 6: Total non-served and dissipated energy throughout the project lifetime for different available budgets in Case A (*top*), Case B (*center*) and Case C (*bottom*).

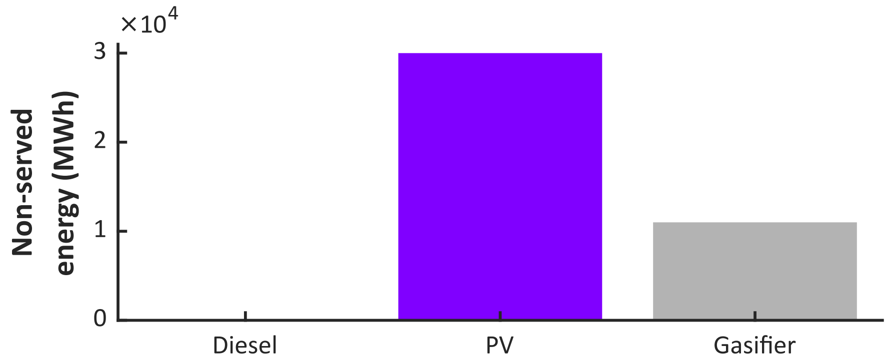

Figure 7: Total non-served energy throughout the project lifetime considering each generation technology individually and Π = 1100 k$.

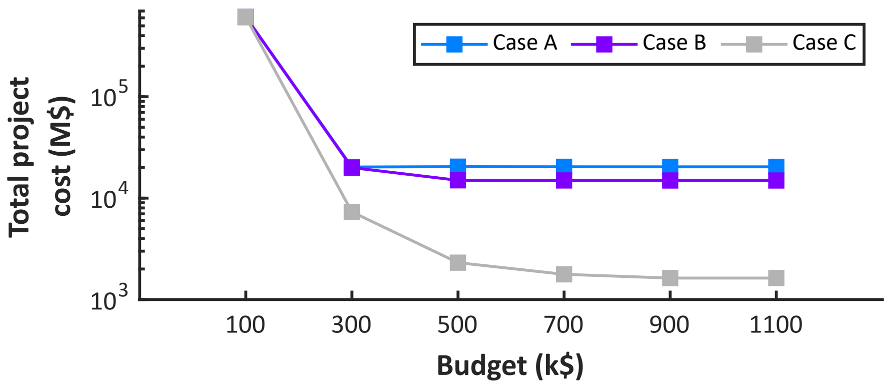

Figure 8: Total project cost for different available budgets in Case A (*top*), Case B (*center*) and Case C (*bottom*).

5.6. *Economic analysis*

Fig. 8 plots the total project cost in the studied cases. As seen, when the available budget is low and the DEG installed power limited to 200 kW, the total project cost is very high due to the cost of non-served energy. Note that non-served energy was penalized in this paper at an arbitrarily high price in order to reduce it at minimum. In contrast, when the non-served energy is reduced down to almost zero, the total project cost decreases in consequence. As expected, the total cost in cases B and C was lower compared with Case A. In particular, the total project cost is reduced by 27% and 92% in cases B and C.

Total cost reduction is more significant in Case C, when the biomass gasifier is installed. This is due to the capability of this technology to provide dispatchable energy at very low cost. Actually, the total cost of biomass and diesel in Case C is analyzed in Table 5. As observed, although the cost of diesel is dominant in all the studied cases, the cost of biomass is various order lower in comparison, despite that the gasifier is the most exploited technology in Case C (see Fig. 3). In addition, the biomass gasification technology produces biochar as by-product, which can be sold to obtain an extra monetary income. As evidenced in Table 5, although the incomes due to biochar sale are significantly lower in comparison with the cost of purchased biomass, this by-product still contributes substantially to improving the system economics.

Table 5: Total diesel, biomass and biochar cost in Case D.

Parameter	**Available Budget (k\$)**					
	100	**300**	**500**	**700**	**900**	**1100**
Fuel cost (M\$)	1.9×10^4	6.7×10^3	1.9×10^3	1.3×10^3	1.2×10^3	1.2×10^3
Biomass cost (M\$)	0	233.7	399.7	344.1	329.9	329.9
Biochar cost (M\$)	0	15.5	25.0	21.9	21.0	21.0

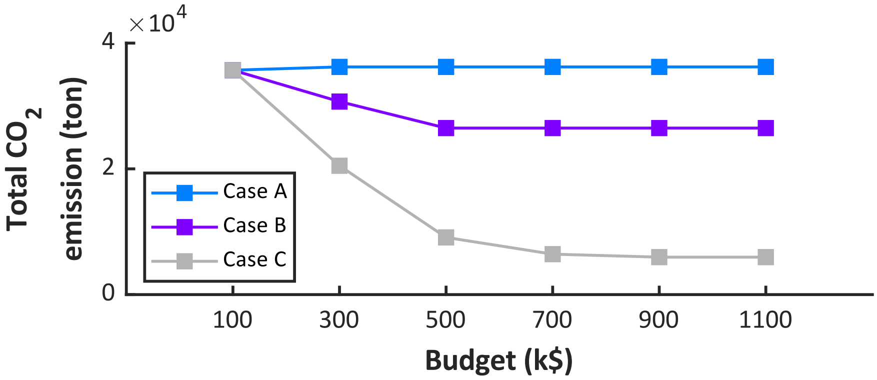

Figure 9: Total CO_2 emissions throughout the project lifetime for different available budgets.

5.7. *Emission analysis*

Reduction of greenhouse gas emission is a major concern nowadays (Liu et al., 2024). In particular, the installation of gasification units allows reducing the size of the DEG, but more notably its yearly energy production. It should be reflected in a drastic reduction of CO_2 total emission. To this end, the total CO_2 emissions in different cases are compared in Fig. 9, considering 0.88 kg CO_2/kWh for the DEG (Mandal et al., 2018). As seen, the installation of PV units in Case B helps to reduce the total emissions by 27% with Π = 1100 k\$, but the reduction is more extreme in Case C when installing a gasification unit, reaching a decrease of 83% compared to Case A. Such decline is also notable when comparing the cases B and C (77% of total reduction), highlighting that the gasification technology contributes to a further decrease in the CO_2 emissions.

5.8. *Sensitivity analysis*

A sensitivity analysis on various input parameters is provided in this section. More specifically, the focus is on the variation of the biomass and biochar cost. To this end, the results are presented only for Π = 1100 k\$. Thus, the effect of the available budget is neglected, since it has already been analyzed in-depth in previous sections. Firstly, the analysis focuses on how the biomass cost affects the planning in Table 6. As expected, an increment in the biomass price leads to an increment in the total project cost. Particularly, the total project costs increments by 33% when the biomass price increases from 0 to 0.4 \$/kg. This is undoubtedly due to an observable increment in the total biomass cost, which grows almost linearly with the biomass price. It demonstrates that gasification is even operated under high biomass prices, thus demonstrating the reliability of this technology. Further, it can be seen that total CO_2 emissions increase (but less notably) with the price of biomass. This result evidences that, even in the scenario of increasing biomass cost, gasifiers remain as the predominant technology in the plant, displacing the use of DEGs.

Table 6: Sensitivity analysis regarding the biomass price

Result	**Biomass price (\$ /kg)**				
	0	**0.1**	**0.2**	**0.3**	**0.4**
Project cost (M\$)	$1.61{\cdot}10^3$	$1.63{\cdot}10^3$	$1.89{\cdot}10^3$	$2.07{\cdot}10^3$	$2.41{\cdot}10^3$
Biomass cost (M\$)	0	329.9	660.6	973.9	1291
Biochar cost (M\$)	25.9	21.0	21.0	20.7	20.6
CO_2 emissions (t)	$5.89{\cdot}10^3$	$5.96{\cdot}10^3$	$5.96{\cdot}10^3$	$6.02{\cdot}10^3$	$6.13{\cdot}10^3$

Next, the impact of the biochar price in final results is analyzed. Thereby, Table 7 is analogue to Table 6, but varying the biochar price, while the biomass cost remains at 0.1 \$/kg. As expected, the total project cost is reduced with the cost of biochar, but its influence is limited in comparison with the biomass cost. It demonstrates that, albeit important, selling biochar is a secondary activity for gasification plants, for which the biomass price is the most significant parameter.

5.9. Scheduling results

Finally, the particular features of each technology are analyzed by studying the scheduling results obtained. It should be noted that one of the advantages of the proposed methodology is that operational limitations of each technology are explicitly modeled, so that ramping or on/off

Table 7: Sensitivity analysis regarding the biochar price

Result	**Biochar price ($ /t)**				
	0	**25**	**50**	**75**	**100**
Project cost (M$)	$1.71 \cdot 10^3$	$1.67 \cdot 10^3$	$1.63 \cdot 10^3$	$1.60 \cdot 10^3$	$1.57 \cdot 10^3$
Biomass cost (M$)	329.5	333.6	329.9	331.3	333.5
Biochar cost (M$)	0	10.6	21.0	31.7	42.48
CO_2 emissions (t)	$5.96 \cdot 10^3$	$5.91 \cdot 10^3$	$5.96 \cdot 10^3$	$5.91 \cdot 10^3$	$5.91 \cdot 10^3$

minimum times are properly included in the model, and thus, the results are close to the real operational features of each technology.

In this regard, Fig. 10 plots the scheduling result for the fifth representative week at the first year of the project horizon (similar results are observed for the remainder representative weeks and years). As observed, the gasifier acts as base load generator, generating near to its rated value almost all the time. This allows notably reducing the use of the DEG, as shown in Fig. 10, corresponding to the Case B. On the other hand, PV generation is restricted to the central hours of the day, when PV potential is not null. During these hours, the gasifier production is typically reduced progressively, in order to meet with the ramp limits that are characteristic of this technology.

5.10. Discussion and recommendation

Throughout Section 5, a number of results and analyses were presented in order to validate the new methodology, as well as showing how the biomass gasification technology helps reducing the total project cost and CO_2 emissions in isolated rural communities. In this regard, biomass gasifiers have revealed its capacity to displace DEG as baseline generation technology. This particularity has a double effect. On the one hand, the total fuel cost is notably reduced, as the cost of biomass is considerably lower than the diesel cost. This result is more significant when considering local biomass generation from agricultural activities, as usual in this kind of communities. On the other hand, CO_2 emissions are notably reduced when installing gasifiers, as a consequence of the total

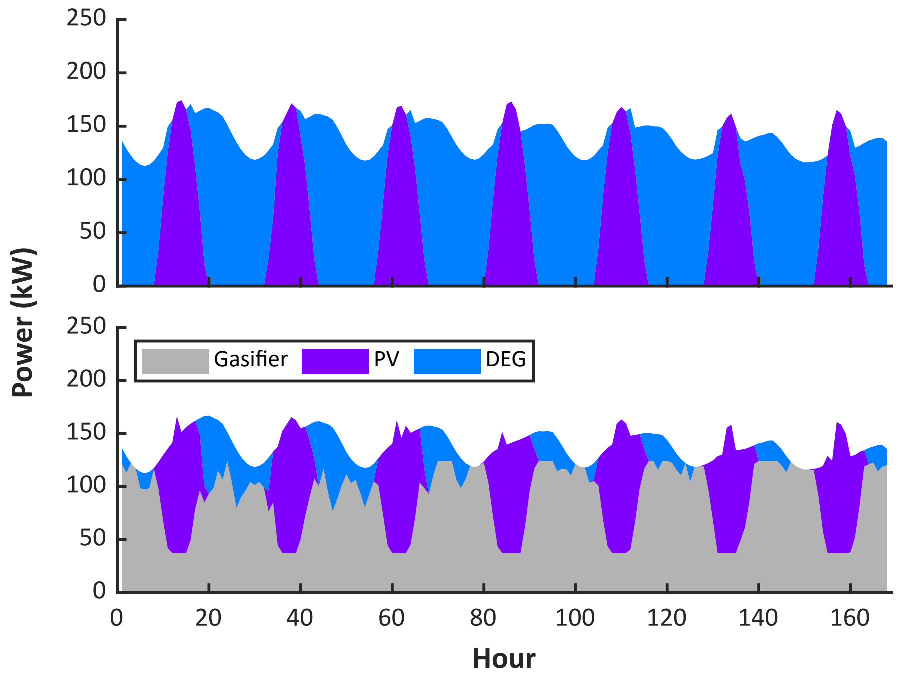

Figure 10: Scheduling results with Π = 700 k\$ in Case B (*top*) and Case C (*bottom*).

energy generated by DEGs, which is significantly reduced. Moreover, as illustrated in Fig. 10, the total working hours of DEGs are drastically reduced when installing gasifiers, which may help to increase the expected lifetime of diesel units and consequently reducing the maintenance requirements of the plant.

From the sensitivity analysis in Section 5.7, it can be concluded that the biomass price has a direct impact on both economic and environmental indicators. In this particular case study, an increment in the biomass cost may lead to an increase in the project cost by 33%. This aspect should be considered by energy planners, thus requiring a careful evaluation of the biomass price in their region and future perspectives since, in the face of unfavorable biomass prices, other clean technologies may be considered alternatively. Nevertheless, it has been shown that gasification remained as the predominant technology, displacing the use of DEGs and thus contributing to both improving the economics and CO_2 emissions of the system. Regarding the biochar price, the sensitivity analysis in Section 5.7 reveals that its effect on final results is limited, only contributing to a marginal reduction in the project cost when the price of biochar increases. In this regard, the sale of biochar can be considered a secondary economic activity for gasifiers.

Based on the outcomes of the study, policies stabilizing biomass prices and promoting sustainable local production are recommended, alongside initiatives to develop biochar markets. Moreover, investing in education and training programs on biomass gasification usage and sustainable agricultural practices would be beneficial for rural communities.

6. Conclusions

A novel methodology for determining the optimal size of hybrid power plants incorporating biomass gasifiers has been developed with the aim of electrifying isolated areas. The new approach considers the particular features of gasifiers in combination with DEGs and PV arrays, such as ramping limits or minimum on/off time. In order to manage large amount of data, a characterization based on representative weeks has been proposed, which properly captures the particular features of gasifiers. Moreover, to make the problem tractable over long planning horizons, a solution strategy based on the multi-cut Benders' decomposition has been implemented.

One of the most salient features of the developed methodology is the consideration of local biomass production from agricultural activities, for which an original algorithm has been developed. In this way, the new proposal is capable to effectively consider the local biomass resource, thus reaching more accurate and reliable results.

The developed methodology has been applied to a benchmark agricultural community in Ghana, devoid of access to the main power grid. The results demonstrate that the incorporation of biomass gasifiers allows reducing the total project cost by over 90% compared to the base case using only DEGs. This remarkable economic saving is attributed to the affordable cost of biomass, which can be complemented by access to local biomass production. The results also show the capability of gasifiers to operate as base load generators, effectively meeting a large portion of the local demand throughout the day. This not only enhances energy access but also contributes to a cleaner and more cost-effective dispatchable local power generation system.

Further results show that gasifiers contribute further to continuous supply than PV units, reducing notably the loss of power supply. Nevertheless, their ramping constraints and other features make them less flexible than DEGs. Moreover, it has been shown that the installation of gasifiers reduces the total CO_2 emissions by 83%, thus constituting a clean alternative to conventional diesel generators. A sensitivity analysis has shown the direct impact of the biomass price in final results, incrementing the project cost by 33% when the biomass price increases from 0 to 0.4 \$/kg. In contrast, the biochar price has a limited impact, only contributing to reducing the project cost marginally when its price increases.

Future works should be focused on developing other related operational models, such as day-ahead scheduling tools or robust approaches for hybrid power plants involving gasifiers.

CRediT authorship contribution statement

M. Tostado-Véliz: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - Original Draft, Writing - Review & Editing. **A. Escámez:** Conceptualization, Investigation, Methodology, Writing - Original Draft, Writing - Review & Editing. **R. Aguado:** Conceptualization, Investigation, Methodology, Writing - Original Draft, Writing - Review & Editing. **D. Sánchez-Lozano:** Conceptualization, Investigation, Methodology, Visualization, Writing - Review & Editing. **F. Jurado:** Funding acquisition, Resources, Supervision, Validation. **D. Vera:** Conceptualization, Funding acquisition, Investigation, Project administration.

Declaration of competing interest

The authors declare no known personal or financial competing interest.

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Appendix A. Linearization of quadratic terms

Given a generic continuous variable ω whose quadratic function needs to be linearized, its quadratic curve is broken into n points described by the pair of values $\left\langle \widetilde{\omega}_j, \left(\widetilde{\omega}_j\right)^2 \right\rangle$. Thus, the quadratic value of this variable can be replaced by the dummy variable z, including the following set of constraints:

$$z \geq L_j \left(\omega - \widetilde{\omega}_j\right) + \left(\widetilde{\omega}_j\right)^2 ; j \in \{1, 2, \ldots, n\} \tag{A.1}$$

where L_j represents the j^{th} slope of the piecewise representation given by:

$$L_j = \frac{\left(\widetilde{\omega}_j\right)^2 - \left(\widetilde{\omega}_{j-1}\right)^2}{\widetilde{\omega}_j - \widetilde{\omega}_{j-1}} ; j \in \{2, 3, \ldots, n\} \tag{A.2}$$

References

Adu-Poku, A., Koku Aidam, G.S., Jackson, G.A., N'tsoukpoe, K.E., Kponyo, J.J., Messan, A., Ikonne, O., Kwarteng, W., Kemausuor, F., 2023. Performance assessment and resilience of solar mini-grids for sustainable energy access in Ghana. Energy 285, 129431. doi:10.1016/j.energy.2023.129431.

Afonaa-Mensah, S., Odoi-Yorke, F., Babatunde Majeed, I., 2024. Evaluating the impact of industrial loads on the performance of solar PV/diesel hybrid renewable energy systems for rural electrification in Ghana. Energy Convers. Manag. X 21, 100525. doi:10.1016/j.ecmx.2024.100525.

Aguado, R., Escámez, A., Jurado, F., Vera, D., 2023. Experimental assessment of a pilot-scale gasification plant fueled with olive pomace pellets for combined power, heat and biochar production. Fuel 344, 128127. doi:10.1016/j.fuel.2023.128127.

Aguado, R., Vera, D., López-García, D.A., Torreglosa, J.P., Jurado, F., 2021. Techno-economic assessment of a gasification plant for distributed cogeneration in the agrifood sector. Appl. Sci. 11. doi:10.3390/app11020660.

Agyekum, E.B., Nutakor, C., 2020. Feasibility study and economic analysis of stand-alone hybrid energy system for southern Ghana. Sustain. Energy Technol. Assess. 39, 100695. doi:10.1016/j.seta.2020.100695.

Ali, S.A., Hussain, A., Haider, W., Rehman, H.U., Kazmi, S.A.A., 2023. Optimal energy management system of isolated multi-microgrids with local energy transactive market with indigenous pv-, wind-, and biomass-based resources. Energies 16. doi:10.3390/en16041667.

Allesina, G., Pedrazzi, S., Allegretti, F., Morselli, N., Puglia, M., Santunione, G., Tartarini, P., 2018. Gasification of cotton crop residues for combined power and biochar production in Mozambique. Appl. Therm. Eng. 139, 387–394. doi:10.1016/j.applthermaleng.2018.04.115.

Alves, O., Calado, L., Panizio, R.M., Gonçalves, M., Monteiro, E., Brito, P., 2021. Techno-economic study for a gasification plant processing residues of sewage sludge and solid recovered fuels. Waste Manage. 131, 148–162. doi:10.1016/j.wasman.2021.05.026.

Ansong, M., Mensah, L.D., Adaramola, M.S., 2017. Techno-economic analysis of a hybrid system to power a mine in an off-grid area in Ghana. Sustain. Energy Technol. Assess. 23, 48–56. doi:10.1016/j.seta.2017.09.001.

Anvari, S., Vera, D., Aguado, R., Jurado, F., Desideri, U., 2023. Developing an off-grid biomass gasification cogeneration system for Moroccan olive oil mills: Simulation, experimental validation, and 3E analysis. Energy Convers. Manag. 298, 117781. doi:10.1016/j.enconman.2023.117781.

Arranz-Piera, P., Kemausuor, F., Darkwah, L., Edjekumhene, I., Cortés, J., Velo, E., 2018. Mini-grid electricity service based on local agricultural residues: Feasibility study in rural ghana. Energy 153, 443–454. doi:10.1016/j.energy.2018.04.058.

Arévalo, P., Tostado-Véliz, M., Jurado, F., 2021. A novel methodology for comprehensive planning of battery storage systems. J. Energy Storage 37, 102456. doi:10.1016/j.est.2021.102456.

Basu, P., 2018. Biomass Gasification, Pyrolysis and Torrefaction. Third ed., Academic Press. doi:10.1016/C2016-0-04056-1.

Campbell, R.M., Anderson, N.M., Daugaard, D.E., Naughton, H.T., 2018. Financial viability of biofuel and biochar production from forest biomass in the face of market price volatility and uncertainty. Appl. Energy 230, 330–343. doi:10.1016/j.apenergy.2018.08.085.

Come Zebra, E.I., van der Windt, H.J., Nhumaio, G., Faaij, A.P., 2021. A review of hybrid renewable energy systems in mini-grids for off-grid electrification in developing countries. Renew. Sust. Energ. Rev. 144, 111036. doi:10.1016/j.rser.2021.111036.

Commission, E., . European Commission Photovoltaic Geographical Information System. https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html. Accessed: November 13, 2023.

Conejo, A., Castillo, E., Minguez, R., Garcia-Bertrand, R., 2006. Decomposition Techniques in Mathematical Programming: Engineering and Science Applications. Springer Berlin Heidelberg.

Constante-Flores, G.E., Conejo, A.J., 2023. Security-constrained unit commitment: A decomposition approach embodying kron reduction. Eur. J. Oper. Res. doi:10.1016/j.ejor.2023.06.013.

Dogru, M., Howarth, C., Akay, G., Keskinler, B., Malik, A., 2002. Gasification of hazelnut shells in a downdraft gasifier. Energy 27, 415–427. doi:10.1016/S0360-5442(01)00094-9.

Erdiwansyah, Gani, A., Zaki, M., Mamat, R., Nizar, M., Rosdi, S., Yana, S., Sarjono, R., 2023. Analysis of technological developments and potential of biomass gasification as a viable industrial process: A review. Case Stud. Chem. Environ. Eng. 8, 100439. doi:10.1016/j.cscee.2023.100439.

Fryda, L., Visser, R., 2015. Biochar for soil improvement: Evaluation of biochar from gasification and slow pyrolysis. Agriculture 5, 1076–1115. doi:10.3390/agriculture5041076.

Fusselman, S., Darby, A., Widman, F., 2006. ADVANCED GASIFIER PILOT PLANT CONCEPT DEFINITION TOPICAL REPORT. Report for DOE Award Number DE-FC26-04NT42237 URL: https://core.ac.uk/download/pdf/71305322.pdf. accessed: November 13, 2023.

Gamil, M.M., Lotfy, M.E., Hemeida, A.M., Mandal, P., Takahashi, H., Senjyu, T., 2021. Optimal sizing of a residential microgrid in Egypt under deterministic and stochastic conditions with PV/WG/Biomass Energy integration. Aims Energy 9. doi:10.3934/energy.2021024.

Gurobi Optimization L.L.C., 2021. Gurobi Optimizer Reference Manual. https://www.gurobi.com. Accessed: November 13, 2023.

Hagos, F.Y., Aziz, A.R.A., Sulaiman, S.A., 2014. Trends of syngas as a fuel in internal combustion engines. Adv. Mech. Eng. 6, 401587. doi:10.1155/2014/401587.

Hansen, V., Müller-Stöver, D., Ahrenfeldt, J., Holm, J.K., Henriksen, U.B., Hauggaard-Nielsen, H., 2015. Gasification biochar as a valuable by-product for carbon sequestration and soil amendment. Biomass Bioenerg. 72, 300–308.

doi:10.1016/j.biombioe.2014.10.013.

Hornung, A., Stenzel, F., Grunwald, J., 2021. Biochar—just a black matter is not enough. Biomass Conv. Bioref. doi:10.1007/s13399-021-01284-5.

International Energy Agency (IEA), . Recommendation 5 of the Global Commission on People-Centred Clean Energy Transitions. https://www.iea.org/reports/recommendations-of-the-global-commission-on-people-centred-clean-energy-transitions/recommendation-5. Accessed: November 13, 2023.

International Renewable Energy Agency (IRENA), 2012. Biomass for Power Generation. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2012/RE_Technologies_Cost_Analysis-BIOMASS.pdf. Accessed: November 13, 2023.

Kazempour, S., Conejo, A., 2012. Strategic generation investment under uncertainty via benders decomposition. IEEE Transactions on Power Systems 27, 424–432. doi:10.1109/TPWRS.2011.2159251.

Kemausuor, F., Ackom, E., 2017. Toward universal electrification in ghana. Wiley interdisciplinary reviews: energy and environment 6, e225. doi:10.1002/wene.225.

Khodayar, M.E., 2017. Rural electrification and expansion planning of off-grid microgrids. The Electricity Journal 30, 68–74. doi:10.1016/j.tej.2017.04.004.

Konneh, K.V., Adewuyi, O.B., Gamil, M.M., Fazli, A.M., Senjyu, T., 2023. A scenario-based multi-attribute decision making approach for optimal design of a hybrid off-grid system. Energy 265, 125663. doi:10.1016/j.energy.2022.125663.

Korzhenevych, A., Owusu, C.K., 2021. Renewable minigrid electrification in off-grid rural ghana: Exploring households willingness to pay. Sustainability 13. doi:10.3390/su132111711.

Lanagran, E., Ortega, M.V., Ortega, M., Vera, D., Jurado, F., 2023. Design of an energy management system applied to an electric power plant based on a biomass gasifier. Renew. Energy 216, 119116. doi:10.1016/j.renene.2023.119116.

Liu, G., Jiang, W., Ma, L., Jin, Y., Guo, W., Li, Q., Li, D., 2024. Research on energy-saving renovation of solar greenhouses based on multiple factors and multiple objectives. J. Clean. Prod. 434, 140239. doi:10.1016/j.jclepro.2023.140239.

Macrotrends Ghana, . Ghana Electricity Access 1993-2023. https://www.macrotrends.net/countries/GHA/ghana/electricity-access-statistics. Accessed: November 13, 2023.

Mandal, S., Das, B.K., Hoque, N., 2018. Optimum sizing of a stand-alone hybrid energy system for rural electrification in Bangladesh. J. Clean. Prod. 200, 12–27. doi:10.1016/j.jclepro.2018.07.257.

Martiny, N., Jossen, A., 2011. Challenges of battery systems in tropical environment.

Martínez, J.D., Mahkamov, K., Andrade, R.V., Silva Lora, E.E., 2012. Syngas production in downdraft biomass gasifiers and its application using internal combustion engines. Renew. Energy 38, 1–9. doi:10.1016/j.renene.2011.07.035.

Mazhkoo, S., Dadfar, H., HajiHashemi, M., Pourali, O., 2021. A comprehensive experimental and modeling investigation of walnut shell gasification process in a pilot-scale downdraft gasifier integrated with an internal combustion engine. Energy Convers. Manag. 231, 113836. doi:10.1016/j.enconman.2021.113836.

Mohamed, A.A., Best, R.J., Liu, X., Morrow, D.J., 2022. A comprehensive robust techno-economic analysis and sizing tool for the small-scale pv and bess. IEEE Transactions on Energy Conversion 37, 560–572. doi:10.1109/TEC.2021.3107103.

Montuori, L., Alcázar-Ortega, M., Álvarez Bel, C., Domijan, A., 2014. Integration of renewable energy in microgrids coordinated with demand response resources: Economic evaluation of a biomass gasification plant by Homer Simulator. Appl. Energy 132, 15–22. doi:10.1016/j.apenergy.2014.06.075.

Moock, N.W., Trapp, W.L., 2000. Patent: Method for the production of .beta.-silicon carbide whiskers from rice hulls. https://patentimages.storage.googleapis.com/df/b3/0f/2df6b036398df7/US6033447A.pdf. Accessed: November 13, 2023.

Moreira, A., Pozo, D., Street, A., Sauma, E., Strbac, G., 2021. Climate-aware generation and transmission expansion planning: A three-stage robust optimization approach. Eur. J. Oper. Res. 295, 1099–1118. doi:10.1016/j.ejor.2021.03.035.

Murshed, M., Ozturk, I., 2023. Rethinking energy poverty reduction through improving electricity accessibility: A regional analysis on selected African nations. Energy 267, 126547. doi:10.1016/j.energy.2022.126547.

Odoi-Yorke, F., Abaase, S., Zebilila, M., Atepor, L., 2022a. Feasibility analysis of solar PV/biogas hybrid energy system for rural electrification in Ghana. Cogent Eng. 9, 2034376. doi:10.1080/23311916.2022.2034376.

Odoi-Yorke, F., Osei, L.K., Gyamfi, E., Adaramola, M.S., 2022b. Assessment of crop residues for off-grid rural electrification options in ghana. Scientific African 18, e01435. doi:10.1016/j.sciaf.2022.e01435.

Odoi-Yorke, F., Woenagnon, A., 2021. Techno-economic assessment of solar PV/fuel cell hybrid power system for telecom base stations in Ghana. Cogent Eng. 8, 1911285. doi:10.1080/23311916.2021.1911285.

Pinto, E.S., Serra, L.M., Lázaro, A., 2020. Evaluation of methods to select representative days for the optimization of polygeneration systems. Renew. Energy 151, 488–502. doi:10.1016/j.renene.2019.11.048.

Prakash, S., Dhal, P., 2022. Cost optimization and optimal sizing of standalone biomass/diesel generator/wind turbine/solar microgrid system. AIMS Energy 10. doi:10.3934/energy.2022032.

Rajbongshi, R., Borgohain, D., Mahapatra, S., 2017. Optimization of PV-biomass-diesel and grid base hybrid energy systems for rural electrification by using HOMER. Energy 126, 461–474. doi:10.1016/j.energy.2017.03.056.

Ramamurthi, P.V., Fernandes, M.C., Nielsen, P.S., Nunes, C.P., 2016. Utilisation of rice residues for decentralised electricity generation in Ghana: An economic analysis. Energy 111, 620–629. doi:10.1016/j.energy.2016.05.116.

Reed, T.B., Das, A., 1988. Handbook of biomass downdraft gasifier engine systems. Biomass Energy Foundation, Golden, CO, US. URL: https://www.nrel.gov/docs/legosti/old/3022.pdf.

Ribó-Pérez, D., Ángela Herraiz-Cañete, Alfonso-Solar, D., Vargas-Salgado, C., Gómez-Navarro, T., 2021. Modelling biomass gasifiers in hybrid renewable energy microgrids; a complete procedure for enabling gasifiers simulation in HOMER. Renew. Energy 174, 501–512. doi:10.1016/j.renene.2021.04.083.

Sackey, D.M., Amoah, M., Jehuri, A.B., Owusu-Manu, D.G., Acapkovi, A., 2023. Techno-economic analysis of a microgrid design for a commercial health facility in Ghana- Case study of Zipline Sefwi-Wiawso. Scientific African 19, e01552. doi:10.1016/j.sciaf.2023.e01552.

Salisu, J., Gao, N., Quan, C., 2021. Techno-economic assessment of co-gasification of rice husk and plastic waste as an off-grid power source for small scale rice milling - an Aspen Plus model. J. Anal. Appl. Pyrol. 158, 105157. doi:10.1016/j.jaap.2021.105157.

Sangadiev, A., Gonzalez-Castellanos, A., Pozo, D., 2022. A review on recent advances in scenario aggregation methods for power system analysis. arXiv:2207.09557.

Sansaniwal, S., Pal, K., Rosen, M., Tyagi, S., 2017. Recent advances in the development of biomass gasification technology: A comprehensive review. Renew. Sust. Energ. Rev. 72, 363–384. doi:10.1016/j.rser.2017.01.038.

Seglah, P.A., Neglo, K.A.W., Wang, H., Cudjoe, D., Kemausuor, F., Gao, C., Bi, Y., Wang, Y., 2023. Electricity generation in Ghana: Evaluation of crop residues and the associated greenhouse gas mitigation potential. J. Clean. Prod. 395, 136340. doi:10.1016/j.jclepro.2023.136340.

Singh, A., Basak, P., 2021. Conceptualization and techno-economic evaluation of microgrid based on PV/Biomass in Indian scenario. J. Clean. Prod. 317, 128378. doi:10.1016/j.jclepro.2021.128378.

Sowe, J., Varela Barreras, J., Schimpe, M., Wu, B., Candelise, C., Nelson, J., Few, S., 2022. Model-informed battery current derating strategies: Simple methods to extend battery lifetime in islanded mini-grids. J. Energy Storage 51, 104524. doi:10.1016/j.est.2022.104524.

Sánchez-Lozano, D., Escámez, A., Aguado, R., Oulbi, S., Hadria, R., Vera, D., 2023. Techno-economic assessment of an off-grid biomass gasification chp plant for an olive oil mill in the region of marrakech-safi, morocco. Appl. Sci. 13. doi:10.3390/app13105965.

Tostado-Véliz, M., Hasanien, H.M., Jordehi, A.R., Turky, R.A., Jurado, F., 2023a. Risk-averse optimal participation of a DR-intensive microgrid in competitive clusters considering response fatigue. Appl. Energy 339, 120960. doi:10.1016/j.apenergy.2023.120960.

Tostado-Véliz, M., Hasanien, H.M., Rezaee Jordehi, A., Turky, R.A., Gómez-González, M., Jurado, F., 2023b. An Interval-based privacy – Aware optimization framework for electricity price setting in isolated microgrid clusters. Appl. Energy 340, 121041. doi:10.1016/j.apenergy.2023.121041.

Tostado-Véliz, M., Kamel, S., Aymen, F., Rezaee Jordehi, A., Jurado, F., 2022a. A Stochastic-IGDT model for energy management in isolated microgrids considering failures and demand response. Appl. Energy 317, 119162. doi:10.1016/j.apenergy.2022.119162.

Tostado-Véliz, M., Kamel, S., Hasanien, H.M., Turky, R.A., Jurado, F., 2022b. A mixed-integer-linear-logical programming interval-based model for optimal scheduling of isolated microgrids with green hydrogen-based storage considering demand response. J. Energy Storage 48, 104028. doi:10.1016/j.est.2022.104028.

Tostado-Véliz, M., León-Japa, R.S., Jurado, F., 2021. Optimal electrification of off-grid smart homes considering flexible demand and vehicle-to-home capabilities. Appl. Energy 298, 117184. doi:10.1016/j.apenergy.2021.117184.

V., A.K., Verma, A., 2021. Optimal techno-economic sizing of a solar-biomass-battery hybrid system for off-setting dependency on diesel generators for microgrid facilities. J. Energy Storage 36, 102251. doi:10.1016/j.est.2021.102251.

Wang, C., Liu, Y., Li, X., Guo, L., Qiao, L., Lu, H., 2016. Energy management system for stand-alone diesel-wind-biomass microgrid with energy storage system. Energy 97, 90–104. doi:10.1016/j.energy.2015.12.099.

Williams, N.J., Jaramillo, P., Taneja, J., Ustun, T.S., 2015. Enabling private sector investment in microgrid-based rural electrification in developing countries: A review. Renew. Sust. Energ. Rev. 52, 1268–1281. doi:10.1016/j.rser.2015.07.153.

Zheng, Y., Jenkins, B.M., Kornbluth, K., Kendall, A., Træholt, C., 2018. Optimization of a biomass-integrated renewable energy microgrid with demand side management under uncertainty. Appl. Energy 230, 836–844. doi:10.1016/j.apenergy.2018.09.015.

Zhou, K., Wang, Y., Hussain, J., 2022. Energy poverty assessment in the Belt and Road Initiative countries: based on entropy weight-TOPSIS approach. Energy Efficiency 15, 1–27. doi:10.1007/s12053-022-10055-8.

Zhou, Z., wang, c., Ge, L., 2019. Operation of stand-alone microgrids considering the load following of biomass power plants and the power curtailment control optimization of wind turbines. IEEE Access 7, 186115–186125. doi:10.1109/ACCESS.2019.2958678.