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Bayesian Inference-Based Energy Management Strategy for Techno-Economic Optimization of a Hybrid Microgrid

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Abstract: This paper introduces a novel techno-economic feasibility analysis of energy management utilizing the Homer software v3.14.5 environment for an independent hybrid microgrid. This study focuses on a school with twelve classes, classifying the electrical components of the total load into three priority profiles: green, orange, and red. The developed approach involves implementing demand management for the hybrid microgrid through Bayesian inference, emphasizing goal-directed decision making within embodied or active inference. The Bayesian inference employs three parameters as inputs: the total production of the hybrid system, the load demand, and the state of charge of batteries to determine the supply for charge consumption. By framing decision making and action selection as variational Bayesian inference, the approach transforms the problem from selecting an optimal action to making optimal inferences about control. The results have led to the creation of a Bayesian inference approach for the new demand management strategy, applicable to load profiles resembling those of commercial and service institutions. Furthermore, Bayesian inference management has successfully reduced the total unmet load on secondary and tertiary priority charges to 1.9%, thereby decreasing the net present cost, initial cost, and energy cost by 37.93%, 41.43%, and 36.71%, respectively. This significant cost reduction has enabled a substantial decrease in investments for the same total energy consumption.

Keywords: energy management; techno-economic optimization; hybrid systems; PV–wind; demand management; microgrid; Bayesian inference

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1. Introduction

Recently, renewable energy systems (RESs) have emerged as highly attractive solutions for mitigating global warming and reducing greenhouse gas (GHG) emissions in the electricity generation sector [1]. The rapid technological and market advancements in renewable energy have led to a significant decrease in the costs of RES components and, consequently, the cost of energy (COE). Moreover, the recent price escalation of fossil-based resources such as oil, gas, and fuel has positioned RES as a competitive alternative to conventional electricity generators [2]. While developed countries have expanded their installed RES capacity due to the decline in costs, economic and financial constraints have impeded this progress in developing countries, especially in Africa. As a result, the installed capacity of RES in Africa accounts for only about 1.97% of the global total [3].

Despite the potential for natural resources suitable for RES installations in African countries, limitations persist, particularly in securing adequate budgets for these projects [4–8]. Enhancing the techno-economic feasibility (TEF) of RES projects in Africa is crucial. This improvement could contribute significantly to addressing the electricity deficit in a continent that harbors over half of the global population without access to electricity, according to the World Bank [9]. It would assist these regions in achieving universal electrical supply goals, reducing the reliance of remote areas on diesel generators (DGs) for electricity production, curbing harmful emissions, and promoting energy generation through sustainable technologies [10].

Hence, harnessing the region's two most abundant and cost-effective renewable energy resources, namely, solar and wind, has become imperative for African countries. Additionally, optimizing the electrical consumption of local communities is essential to ensure a cost-effective electrical supply [11,12]. Solar and wind, as renewable sources, can complement each other to some extent. Wind energy, for example, can compensate for the lack of daylight in electricity production [13]. However, their availability may only sometimes be sufficient to meet the electricity demand. Therefore, their utilization often requires support from other systems, commonly a storage bank and/or a diesel generator. While electrochemical storage is typically preferred over diesel generators to increase renewable energy penetration and avoid greenhouse gas (GHG) emissions [14], it remains a costly component of hybrid renewable energy systems. Oversizing electrochemical storage significantly impacts the net present cost (NPC) and the cost of energy (COE) of the entire system [15].

The International Renewable Energy Agency (IRENA) posits that electrical production from renewable sources in Africa can competitively meet the growing energy consumption, contributing to energy security and effective participation in the global energy transition [16]. This is particularly crucial for continents where attracting sufficient finance for renewable energy investments poses a significant challenge [17]. In Africa, electrical supply ranks among the top five priorities for local development, as identified by the African Development Bank (AfDB). Nevertheless, the lack of funding and investments in renewable energy projects has constrained the economic feasibility of RES, as evident in various studies [17,18].

Hafner et al. [19] highlight that the estimated potential for solar and wind energy in Africa is 1000 GW and 110 GW, respectively, according to the AfDB. However, the continent lags significantly in the policy and finance aspects of renewable energies, with only USD 8 billion invested annually. As a result, Africa is far from meeting the required annual investment budget of USD 70 billion by 2030 for the electricity sector and energy transition to achieve global objectives. Encouraging private investments in the green energy sector and securing support from international financial institutions becomes essential to facilitate this energy transition while ensuring an affordable COE for users [20].

Edward et al.'s work [10] identifies insufficient funding as hindering the energy transition. Despite increasing global financing to combat climate change, funding for renewable energy projects remains inadequate for the African continent [17,21]. Closing this financial gap requires adapting investment policies and streamlining administrative procedures, as local governments encourage the private sector to cover only 10% of energy investments in Africa [22]. Moreover, improved co-operation between African countries is essential to reduce political barriers and expedite the energy transition [23]. Osiolo [3] underscores that despite the remarkable growth in renewable energy investments from USD 45.2 billion in 2004 to USD 303.5 billion in 2020 and the promising returns expected from investments in the electrical production sector using renewable sources in Africa, the continent still faces challenges due to the high initial cost of installing such systems [23,24]. These initial costs can be mitigated at the expense of comfort in some remote regions where economic feasibility precedes technical considerations [25].

According to the International Energy Agency (IEA), the building sector consumes 40% of globally produced energy [23]. Commercial and service institutions, particularly heating, cooling, and lighting systems, are significant consumers of energy budgets. State coverage for non-profit institutions, such as public schools and hospitals, underscores the need to rationalize energy consumption and reduce costs, aligning with global energysaving plans [26,27]. The integration of control systems, especially those based on artificial intelligence (AI), plays a pivotal role in managing electrical load demand, correlating it with energy production, and optimizing the temporal cost of energy (COE) [28]. The optimal integration of solar (thermal or photovoltaic (PV)) and wind systems, coupled with storage systems, reduces the dependence on conventional energy sources [29]. Implementing energy management techniques in renewable energy systems (RES) enhances microgrids' energy efficiency and stability, reducing peak load and energy costs by aligning consumption patterns with RES production [30,31].

The novel contribution of this research lies in its innovative application of variational Bayesian inference for energy management in a hybrid microgrid, utilizing decision making and action selection. This approach uniquely integrates heuristics derived from decision theory in psychology and expected utility theory in economics into the embodied or active inference framework. This novel approach thus provides a unique perspective on decision making in energy management within a hybrid microgrid.

The structure of this work is organized as follows: The introduction is presented in the first section, followed by a literature review emphasizing the original contributions. This is followed by a detailed elaboration of the methodology in the following section. The following section outlines the results and discusses the outcomes obtained. The conclusion of this work is encapsulated in the last section.

2. Literature Review and Original Contributions

Integrating energy management techniques into renewable energy systems (RESs) improves microgrids' energy efficiency and stability. This implementation reduces peak loads and energy costs by aligning consumption patterns with producing renewable energy sources.

Recent works, such as that of Babaei et al. [32], emphasize the critical role of demand management (DM) in ensuring power system reliability for standalone buildings, particularly in remote areas reliant on diesel generators (DGs) for electricity [32,33]. Therefore, the transition to PV–wind hybrid systems, proven to be the best alternative for electrical production in such areas, should be accompanied by DM systems [34,35]. This process has significantly improved unsupplied load and extra power generation by 78% and 61%, respectively [36]. Combining microgrids with DM systems operating in grid and off-grid modes has demonstrated advantages in numerous residential and commercial applications [37,38]. DM systems aim to reduce consumption during peak hours, increase the penetration of renewable energies, and limit the dependence on grid purchases. Applying load planning mechanisms has effectively managed the demand for residential loads.

Additionally, swarm-based intelligent methods, as demonstrated by Feng et al. [39], prove effective in solving engineering problems. Abdelrahman et al.'s literature review [40] emphasizes the advisability of using RESs in microgrids. Therefore, whether residential or commercial, DM for these microgrids is crucial for transforming them into smart microgrids (SMG), monitoring the building's electrical consumption and daily operations, and adapting them to electrical production. A recent study by Rona et al. comprehensively examined energy management systems, focusing on distributed generation, control methods, and microgrid configurations for reliable hybrid renewable energy. It also highlighted the need for robust optimization algorithms, hardware-in-the-loop validation, and data privacy in networked microgrids for future research in energy management [41]. The case study conducted by Ma and Yuan explored the integration of hybrid renewable energy systems in green buildings, focusing on the optimal design and comparison of photovoltaic panels with two storage systems: PV/battery and off-grid PV/hydrogen. Using particle swarm optimization (PSO) in MATLAB, it focuses on designing the system for minimum total annual cost (TAC) and maximum reliability [42].

Load uncertainties pose a significant challenge to the scheduling of microgrids, affecting their operation to improve energy accessibility and efficiency at a low cost. Hence, it is essential to consider these uncertainties in RES smart microgrids [43,44]. Mansouri et al.'s work [45] addresses uncertainties in load scheduling, achieving a robust schedule in the face of consumption fluctuations. Various methods showed a 5.65% decrease in operating costs, significantly increasing the consumer comfort index. Automatic switching further reduced the total cost of operation by 9.71% and increased the consumer comfort index by approximately 0.2%. Considering the stochastic availability of renewable resources, Komala [46] highlights the challenge of balancing electrical production from standalone RES and load demand. Electrochemical storage was identified as a facilitator in managing such electrical systems. Saffar and Ahmad's work [47] proposes a new energy management system that achieved a 65% reduction in operating costs and a 96% reduction in unsupplied energy using dump load and electric vehicles.

Integrated programming models in autonomous RES, as developed by Kiptoo et al. [48], demonstrated the optimization of microgrids under different DM strategies. Wang et al. [49] proposed a DM method based on the produced power of a grid-connected RES equipped with electrochemical storage, considering the uncertainties of renewable resources. Sarker et al. [50] used a swarm-based algorithm in MATLAB to reduce household electricity expenses by shifting loads to periods of lower electricity prices, maximizing energy consumption from renewable sources. Vincent et al.'s [51] numerical results showed that using a prediction corrector model and Markov chains with local scaling improves the satisfaction rate, particularly for microgrids with low storage capacity. Their proposed model, especially when using 100 kWh storage, is 2.8% more cost-effective, confirming that batteries mitigate the poor performance of baseline prediction models.

DM and technical–economic optimization strategies of RESs must be precise and adapted to the site characteristics where the microgrid is installed. Artificial intelligence (AI) methods such as genetic algorithms and neural networks, as developed by Leonori et al. [52,53], can be utilized to test and validate these two aspects. The actual reduction in the cost of RES components is expected to make the COE produced by competitive renewable resources even lower than that produced by conventional fossil fuels shortly [54]. In the United States, the COE generated by photovoltaics has declined to less than 2.5 CAD/kWh, reaching a world-record low of 2.175 CAD/kWh in Idaho, with an anticipated 66% drop by 2040 [55]. Terrestrial wind turbines (WTs) in the same country have a COE not exceeding 2 CAD/kWh, which is expected to decrease by 47% by 2040 for WTs [56]. However, despite the 85% decrease recorded between 2010 and 2018 in the COE produced by lithium-ion (Li-Ion) batteries, reaching 18.7 CAD/kWh [57], electrical storage remains more expensive than other energy sources in RES. Still, it is a barrier to realizing RESs [58]. Some European governments financially support electrical storage for RES, leading to the installation of batteries in 40% of small-scale PV systems in Germany. In remote areas, batteries provide various services at a competitive cost, with further cost reductions expected for high-performance technologies like Li-ion batteries, projected to drop by 54% by 2030 [59]. Pascual et al.'s actual conditions test [60] of the DM strategy resulted in a 25% reduction in battery capacity without affecting power availability and microgrid stability, significantly reducing NPC and COE [61].

This study aims to devise an innovative demand management (DM) strategy tailored for commercial and service institutions and apply it to the technical–economic optimization of standalone PV–wind hybrid systems. The proposed DM model is designed to prevent oversizing the storage bank by accounting for irregular load peaks, thereby addressing a critical economic challenge for renewable energy systems (RESs). Since the storage component often bears the highest cost of energy (COE) in microgrids, this approach aims to reduce the net present cost (NPC) and COE, enhancing the feasibility of such systems in financially constrained regions like Africa. Importantly, these improvements are targeted without impacting daily consumption patterns and consumer comfort.

The novel contribution of this work lies in the application of decision making and action selection as variational Bayesian inference for energy management in a hybrid microgrid. This approach seeks to integrate heuristics from decision theory in psychology and expected utility theory in economics within the framework of embodied or active inference [62]. For instance, if faced with a hot object, the immediate reflex would be to withdraw. However, considering certain beliefs, such as the sacred nature of the object, some may choose to endure the heat and retain contact, minimizing exposure. We assume that policies are selected based on the belief that they minimize the disparity between a probability distribution over reachable states and the states that agents believe they should occupy [63,64]. Thus, choices are made based on beliefs regarding alternative policies [65].

3. Development of the Energy Management Strategy

3.1. Presentation of the Project Profiles

The institution to be supplied by our standalone PV–wind hybrid system is a 12-class primary school, situated at a latitude of 31°40′46″ north and a longitude of 2°16′11″ west, in Bechar, Algeria, with a total daily load consummation of 293.16 kWh/d and a peak of 51.52 kW. The technical–economic optimization of this system will be achieved in the HOMER software environment, using the following components: EO10 wind turbine, SPR-X21 PV panels, OPzV 3000 batteries, and a Fron24 inverter/charger, as presented in the schema of Figure 1.

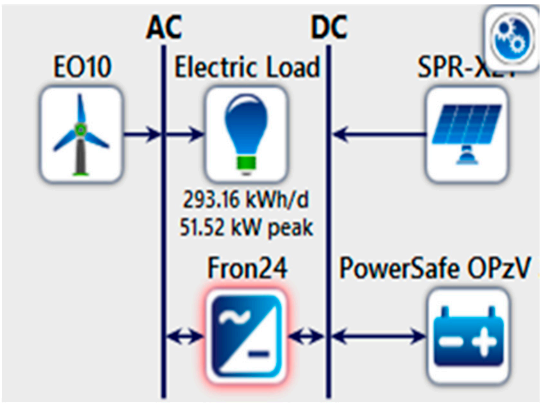


Figure 1. Scheme of a regular configuration of the hybrid PV–wind system.

In this work, the electrical components of the total load are classified into three priority profiles:

- Profile 1 (green): the RES should always satisfy the priority load.
- Profile 2 (orange): the secondary load will be satisfied most of the time by RES, excluding the times that it causes an irregular peak in the total load so that it will be ignored during these periods.
- Profile 3 (red): the third priority load will be considered a deferrable load and will be satisfied only when there is an excess of produced energy, and the first two loads are already satisfied.

For the rest of the work, the total load of 104,964 kWh/year, the total daily load 293.16 kWh/d, and a peak of 51.52 kW will be classified into the following three priorities:

a. The prime priority regroups the lighting of the classrooms and the administrative desks, the electrical plugs of the teacher's office, and the desktops of the administrative officers, with a total load of 50,638 kWh/year, a daily load consumption of 138.75 kWh/d, and a peak of 22.79 kW.
b. The second priority regroups heating/cooling, water pumping, maintenance workshop, and other classroom plugs, with a total load of 42,312 kWh/year, a daily load consumption of 119.81 kWh/d, and a peak of 22.65 kW.
c. The third priority regroups watering, billboards, water fountains, load-shedding plugs, and a plug for an electric vehicle, with a total load of 12,014 kWh/year, a daily consumption of 34.60 kWh/d, and a peak of 6.08 kW.

It is mentioned that the total daily consumption (TDC) of 293.16 kWh/d is approximately the summation of the three priorities. In addition, the total peak of 51.52 kW is the summation of the three priority peaks.

The optimization of the RES according to our new DM strategy will follow multiple steps. First, all components will be sized for the prime priority load of 138.75 kWh/d, as always to satisfy this load, as shown in Figure 2.

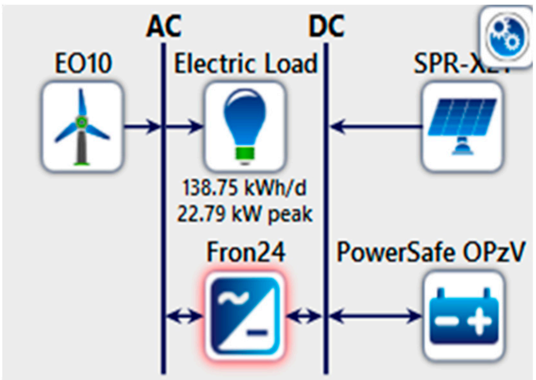


Figure 2. Scheme of the prime priority system.

Optimization results of the configuration schematized in Figure 2 above are resumed in a table of results, presented in Figure 3.

Architecture					Cost			
SPR-X21 (kW)	EO10	PowerSafe OPzV 3000	Fron24 (kW)	Dispatch	NPC ($)	COE ($)	Operating cost ($/yr)	Initial capital ($)
50.7	1	12	31.1	CC	$51,587	$0.0797	$1,564	$31,593

Figure 3. Results table of prime priority sizing.

3.2. Use of Bayesian Inference Approach

The outcomes depicted in Figure 3 will serve as the basis for constructing a Bayesian inference approach for the novel demand management (DM) strategy, designed to handle load profiles akin to those encountered in commercial and service institutions. The Bayesian inference model will take three parameters as inputs: the total production of the renewable energy system (RES), load demand, and the state of charge of batteries. These parameters will guide decisions regarding the supply of load consumption. The highest priority charge is consistently fulfilled, and when there is surplus production to charge batteries and the second priority charge is met, both the primary and secondary loads will be addressed. Subsequently, the deferrable load (third priority) will be attended to whenever excess energy is generated.

To draw parallels between the developed system in this study and human cognition, we traverse three key points:

1. Generative Models: The initial step involves creating generative models to generate a range of choices, representing whether certain charges should be satisfied. Distinguishing between actions, the physical state of the real world, and beliefs about the action, termed "states of control" (control states), transforms the problem from selecting an optimal action to realizing an optimal inference about control. This perspective shifts the focus from optimal action selection to making optimal inferences about control.

2. Belief Development: As choices are rooted in beliefs about policies, these beliefs need to be associated with optimized confidence or precision. This introduces a unique and Bayes-optimal sensitivity or inverse temperature akin to SoftMax choice rules and quantal response equilibria (QRE) [66]. Rules are formulated with an order of parameters, where

the control states encompass the total production of the hybrid system, load demand, and the state of charge of batteries. For instance, the policy might dictate not only satisfying the main load if the battery is at 80% and production is at 50%. If production increases, the system remains in this state until reaching over 80% for load and over 80% for production. At this point, the system transitions to satisfying all load demands, maintaining this mode until the load is below 50% and production is below 40%. This approach introduces the concept of hidden states residing at the fuzzy boundaries of values rather than fixed values (e.g., 80% or 40%), as illustrated in the schema in Figure 4.

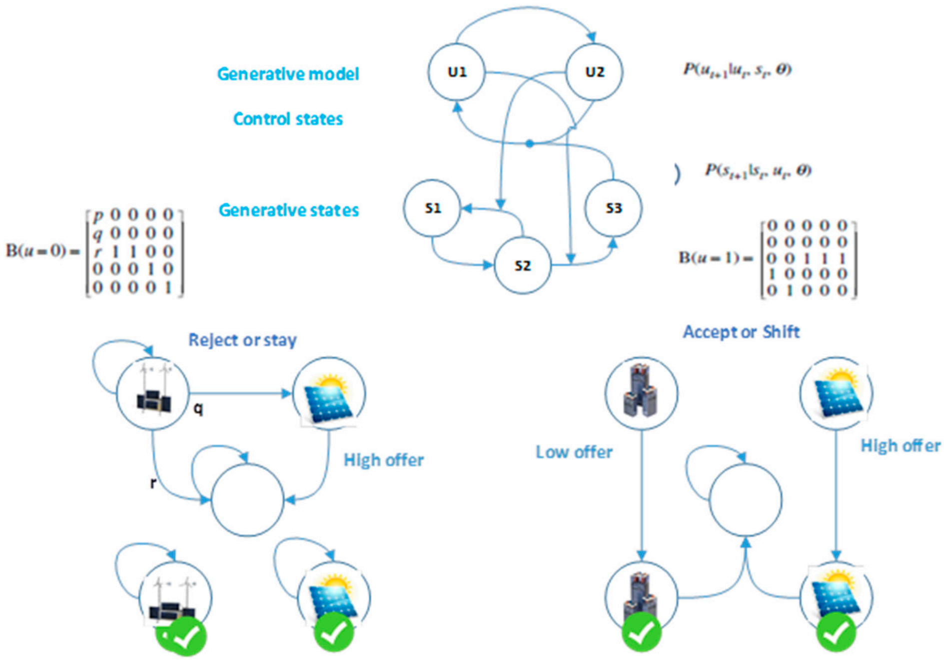


Figure 4. Organigram of system.

3. State of the system: The third point involves acknowledging the system's current state and recognizing the bidirectional relationship between beliefs about rules and the current state of the world. This interdependence introduces an inherent optimism bias [67].

The Bayesian inference method proposed in this work seamlessly aligns with the outlined energy management scenario. Here, Bayesian inference is harnessed for decision making regarding the energy supply for various load types, relying on three pivotal inputs: the total production of renewable energy sources (RESs), the priority of the charge, and the state of charge of the batteries.

Prioritization ensures that the green charge always takes precedence, receiving a continuous and guaranteed energy supply. Surpluses are then directed to fulfill the secondary charge (orange). The tertiary load (red), categorized as a deferrable load, is processed only when surplus energy is available after meeting the first two priority loads. Bayesian inference guides this decision-making process, providing probabilistic evaluations of the system's state and available resources.

3.3. Development of Beliefs about Rules

Belief development is associated with optimized confidence or accuracy, which ties in with the Bayesian nature of the approach, where beliefs are updated based on evidence:

- The inputs taken into consideration for decision as control states.
- The politics of decisions or states of control as hidden states.

For this, we must make a call to the Thompson sampling process, as explained by the following equations [65]:

$$\left.\begin{array}{l}\mu_t = argmin_\mu F\left(\widetilde{o},\mu\right)\\ Pr(a_t = u_t) = Q(u_t|\mu_t)\\ F\left(\widetilde{o},\mu\right) = D_{KL}\left[Q\left(\widetilde{s},\widetilde{u}\middle|\mu\right)\middle\|P\left(\widetilde{s},\widetilde{u}\middle|\widetilde{o}\right)\right] - lnP\left(\widetilde{o}|m\right)\end{array}\right\} \tag{1}$$

The parameters (expectations) of categorical distributions over discrete states s ϵ {1, ... J} are denoted by J * 1 vectors $\widetilde{s}$ ϵ [0, 1], while the ∼ notation denotes sequences of variables over time.

Approximate posterior beliefs about hidden states S ϵ U are encoded by expectations m ϵ Rd.

Ω: a finite set of observations.
SxA: a finite set of true states and actions
SxU: a finite set of fictive or hidden states
R($\widetilde{o}$,$\widetilde{s}$) = Pr({o0, ..., ot} = $\widetilde{o}$, {s0, ..., st} = $\widetilde{s}$, {a0, ..., at} = $\widetilde{a}$): A generative process over observations, states and action.
P($\widetilde{o}$,$\widetilde{s}$,$\widetilde{u}$\m) = Pr({o0, ..., ot} = $\widetilde{o}$,{s0, ..., st} = $\widetilde{s}$,{ut, ..., uT} = $\widetilde{u}$): A generative model over observations and hidden states.

An approximate posterior probability over hidden states with expectations μϵR such that Q($\widetilde{s}$,$\widetilde{u}$\μ) = Pr({s0, ..., st} = s,{ut, ..., uT} = $\widetilde{u}$).

The agent's generative model of observations P($\widetilde{o}$,$\widetilde{s}$,$\widetilde{u}$\m) and its approximate posterior distribution over their causes Q($\widetilde{s}$,$\widetilde{u}$\μ) does not refer to the process of eliciting outcomes through action R($\widetilde{o}$,$\widetilde{s}$,$\widetilde{a}$).

To couple the agent to its environment, we have to specify how its expectations depends upon expectations.

In active inference, the expectations minimize free energy and the ensuing beliefs about control states prescribe action.

The environment is characterized as a distribution R($\widetilde{o}$,$\widetilde{s}$,$\widetilde{a}$) over observations, true stated and action, whereas the agent is characterized by two distributions: a generative model P($\widetilde{o}$,$\widetilde{s}$,$\widetilde{u}$\m) that connects observations to hidden states and posterior beliefs about those states Q($\widetilde{s}$,$\widetilde{u}$\μ) parametrized by its expectations.

$$\left.\begin{array}{l}P\left(\widetilde{o},\widetilde{s},\widetilde{u},y\middle|\widetilde{a},m\right) = P\left(\widetilde{o}\middle|\widetilde{s}\right)P\left(\widetilde{s},\widetilde{u}\middle|y,\widetilde{a}\right)P(y|m)\\ P\left(\widetilde{o}\middle|\widetilde{s}\right) = P(o_0|s_0)P(o_1|s_1)...P(o_t|s_t)\\ P\left(\widetilde{s},\widetilde{u}\middle|y,\widetilde{a}\right) = P\left(\widetilde{u}|s_t,y\right)P(s_t|s_{t-1},a_{t-1})...P(s_1|s_0,a_0)P(s_0|m)\\ lnP\left(\widetilde{u}|s_t,y\right) = y.Q\end{array}\right\} \tag{2}$$

$$Q\left(\widetilde{u}|s_t\right) = \underbrace{H\left[P\left(s_T\middle|s_t,\widetilde{u}\right)\right]}_{exploration_{bonus}} + \sum_{s_T}\underbrace{P\left(s_T\middle|s_t,\widetilde{u}\right)c(s_T|m)}_{expected_{utility}} \tag{3}$$

Rules governing control states, which include the total hybrid system output, charging demand, and battery state of charge, are established to guide decision making. These rules dynamically adapt based on the current state of the system, ensuring efficient energy allocation.

The size of the storage system obtained in the first simulation which contains 12 batteries "model OPzV 3000" will be imposed in the next simulation. Then, the same components of the RES will be sized to satisfy the new main daily load estimated at 258.56 kWh/d with a peak of 45.44 kW that includes the following at the same time:

- A primary load of 138.75 kWh/d and a peak of 22.79 kW.

- A secondary load of 119.81 kWh/d and a peak of 22.65 kW.

In addition, a deferrable daily third priority load of 34.60 kWh/d with a peak of 4.80 kW will be supplied when the main load is satisfied, as presented in the schema of Figure 5.

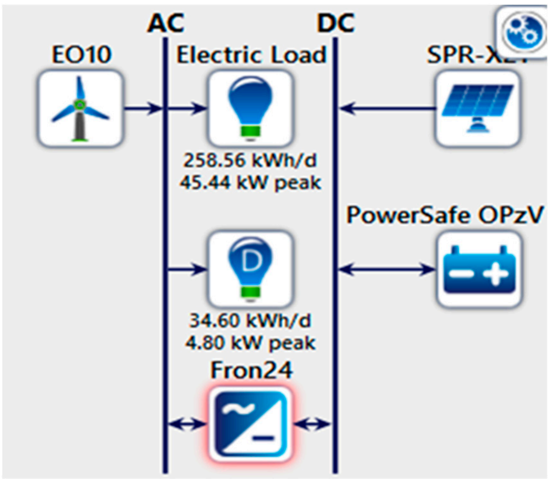
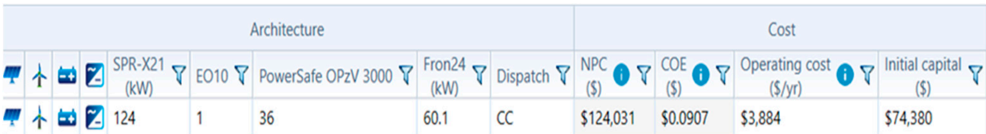


Figure 5. Scheme of the new proposed configuration.

4. Results and Discussion

The first analysis is performed for the original system depicted in Figure 1. Applying standard HOMER software optimization of this original RES, we obtain the following architecture and cost results, presented in Figure 6 and Table 1.



Architecture									Cost			
				SPR-X21 (kW)	EO10	PowerSafe OPzV 3000	Fron24 (kW)	Dispatch	NPC ($)	COE ($)	Operating cost ($/yr)	Initial capital ($)
				124	1	36	60.1	CC	$124,031	$0.0907	$3,884	$74,380

Figure 6. Results table of a standard sizing system.

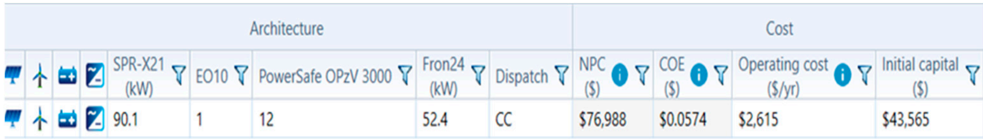
Table 1. Component costs for the standard configuration system.

Component	Capital	Replacement	O&M	Salvage	Total
Battery [USD]	32,400.00	10,102.47	9204.02	5661.87	46,044.62
WT [USD]	5000.00	0.00	639.17	155.33	5483.84
PV [USD]	30,969.43	0.00	31,671.46	0.00	62,640.89
Inverter [USD]	6010.73	4445.96	0.00	595.21	9861.48
System [USD]	74,380.16	14,548.43	41,514.65	6412.41	124,030.83

The optimized system comprises a PV generator of about 124 kW, 1 wind turbine, 36 batteries, and an inverter of 60.1 kW. The NPC of this configuration is estimated at 124,031 USD, of which 74,380 USD is the initial capital, and the COE produced by this system is estimated at 9.07 cent USD/kWh. The costs of components and the whole optimized standard system are presented in Table 1.

Financial results show that the NPC of the whole system is estimated at 124,030 USD, of which the cost of the PV generator and electrochemical storage represent 51% and 37%, respectively, of the NPC.

The second analysis is performed for the new configuration depicted in Figure 5. We apply again the standard HOMER software optimization of this new RES configuration. The architecture and cost results are presented in Figure 7 and Table 2. Thus, the initial capital cost is currently 60% of the original NPC, as presented in the table in Figure 7.



Architecture									Cost			
				SPR-X21 (kW)	EO10	PowerSafe OPzV 3000	Fron24 (kW)	Dispatch	NPC ($)	COE ($)	Operating cost ($/yr)	Initial capital ($)
				90.1	1	12	52.4	CC	$76,988	$0.0574	$2,615	$43,565

Figure 7. Results table of the new sizing.

Table 2. Component costs for the new proposed configuration.

Component	Capital	Replacement	O&M	Salvage	Total
Battery [USD]	10,800.00	4414.09	3068.01	935.87	17,346.23
WT [USD]	5000.00	0.00	639.17	155.33	5483.84
PV [USD]	22,525.00	0.00	23,035.61	0.00	45,560.61
Inverter [USD]	5240.00	3875.87	0.00	0.00	8596.98
System [USD]	43,565.00	8289.96	26,742.78	1610.09	76,987.65

The optimized system comprises a PV generator of 90.1 kW, 1 wind turbine, 12 batteries, and an inverter of 52.4 kW. The NPC of this configuration is estimated at 76,988 USD, of which 43,565 USD is the initial capital, and the COE produced by this system is estimated at 5.74 cent USD/kWh. The costs of the components and the whole optimized new system are resumed in Table 2.

Financial results show that the NPC of the whole system is estimated at 76,988 USD, of which the cost of the PV generator and electrochemical storage represent 59% and 23%, respectively, of the NPC. Thus, the initial capital cost represents 57% of the NPC.

4.1. Comparison of Results

To show the benefit of the new DM strategy on the technical–economic feasibility of PV–wind hybrid systems, we first start comparing the sizes of the components for the regular system and the one with the new DM strategy. The sizes of components are resumed in Table 3.

Table 3. Component size comparison table for the two configurations.

	Standard	New
PV [kW]	124	90.1
WT [units]	1	1
Batteries [units]	36	12
Inverter [kW]	60.1	52.4

Our new DM strategy helped minimize all of the components' sizes, except for the WT, which did not change. The size of the PV generator, the batteries, and the inverter was reduced by 27%, 67%, and 13%, respectively.

These reductions were due to the ignorance of strange peaks of loads generally caused by the cooling system included in the second priority load in our new DM strategy. Table 4 summarizes the electrical critical results of the two configurations which are as follows:

- The total energy consumed by the load in the standard configuration is just one AC load; in the new configuration, it includes primary, secondary, and tertiary loads.
- Capacity shortage.
- Unmet energy.

Table 4. Results comparison table from the two configurations.

	Standard	New
Energy consumed [kWh/year]	106,990	104,964
Capacity shortage [kWh/year]	105	10,172
Unmet energy [kWh/year]	13	2040

Component size minimizations led to a reduction in the total energy consumed by almost 2%. This rate represents the yearly unmet load on the orange and red loads. It also raised the capacity shortage rate from practically 0% to almost 10%, as shown in the energetic graph comparison between the two systems presented in Figure 8 below.

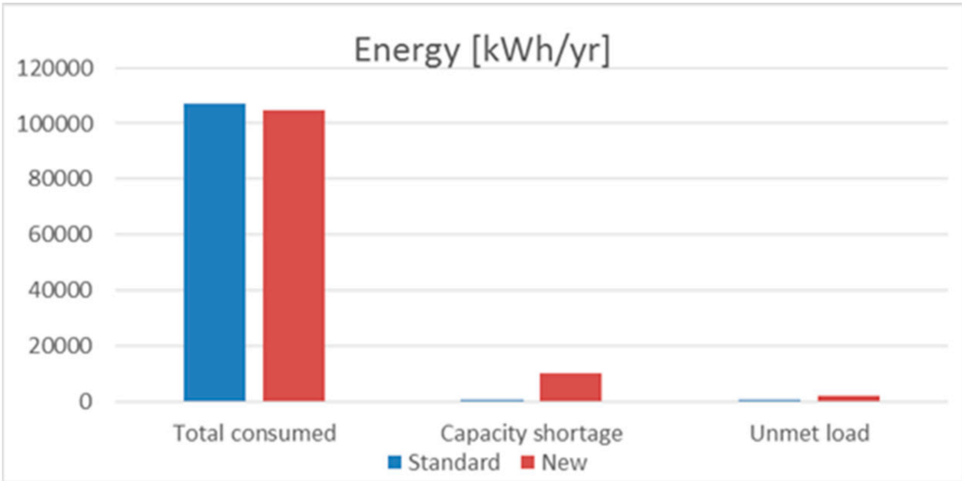


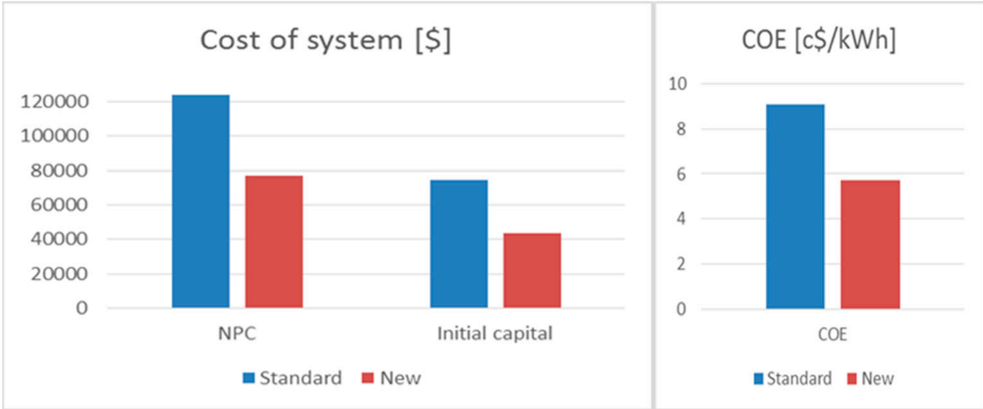
Figure 8. Comparison of energy results.

The new system configuration did not affect only the electrical results; it also significantly affected the economic ones. Each system's NPC, initial cost, and COE are resumed in the following Table 5.

Table 5. Cost size comparison table.

	Standard	New
NPC [USD]	124,036	76,988
Initial cost [USD]	74,380	43,565
COE [cent USD/kW]	9.07	5.74

Compared to the standard configuration, the new configuration demonstrates a significant reduction in NPC, initial cost, and COE, respectively, from 124,036 USD to 76,988 USD, from 74,380 USD to 43,565 USD, and from 9.07 cent USD/kW to 5.74 cent USD/kW. This indicates that the new configuration is more profitable and financially efficient. Figure 9 below presents the comparison graphs of the cost results between the two configurations.



(**a**) (**b**)

Figure 9. Comparison graphs of cost results for the two configurations: (**a**) cost of system; (**b**) COE.

4.2. Bayesian Inference Analysis

Due to 1.91% of unmet load being registered in the new configuration of the system, and to maintain the prime load satisfied at all times, a Bayesian inference will be created to dispatch that unmet load between the second and the third priority loads. In the case that there is not enough production to satisfy the total load, the third priority load will be first disconnected, and then the second priority load. This new DM strategy using Bayesian inference permits the dispatch of the served and unmet loads estimated at 104,964 kWh/year and 2040 kWh/year, respectively. The total unmet load is estimated as follows:

- 1425 kWh/year on 42,312 kWh/year of orange load;
- 615 kWh/year on 12,014 kWh/year of red load.

These results are presented in the following table (Table 6).

Table 6. Profile priorities comparison table.

	Served	Unmet
Prime	100%	0%
Secondary	96.63%	3.37%
Tertiary	94.88%	5.12%

Table 6 shows that the prime load on the new configuration is always served as the standard configuration, and the second load is served 96.63% of the time, while the tertiary load is served 94.88% of the time, so the unmet load will represent 3.37% on the orange profile and only 5.12% on the red profile.

This comparison strongly supports the adoption of the new DM-based Bayesian inference that sacrifices 1.91% of load satisfaction on secondary and tertiary load profiles to gain 37.93%, 41.43%, and 36.71%, respectively, on the NPC, initial cost, and COE as the superior choice for the energy system.

5. Conclusions

This paper introduces a novel approach to energy management in a hybrid microgrid system, employing decision making and action selection through variational Bayesian inference. The strategy significantly reduces peak load and electricity costs by choosing alternative policies. The critical concept involves formulating the problem to create choices, proposing three charge categories (prime, second, and tertiary), each with different shedding characteristics.

The decision-making process is guided by politics that consider supply, demand, and priority factors. The system can remain in its current state or transition to another state, guided by politically beneficial decisions. The energy management strategy is applied to dimension a PV–wind hybrid system supplying a primary school in desert and remote regions, using the Homer software environment.

This innovative strategy substantially reduces net present cost (NPC), initial capital, peak load, and electricity costs. The guarantee of no shedding encourages investments. Bayesian inference management, with a total unmet load of 1.9% on secondary and tertiary priority charges, leads to a remarkable reduction in NPC, initial cost, and cost of energy (COE) by 37.93%, 41.43%, and 36.71%, respectively.

Using Bayesian inference provides a robust framework for decision making in energy management, allowing adaptive resource allocation to different priority loads. This ensures the fulfillment of critical loads while optimizing energy utilization. The emphasis on probabilistic beliefs aligns well with the inherent energy production and consumption uncertainties. Despite that, it presents some limits, such as dependence on the quality of the data, computational complexity if these data are extensive, and subjectivity in the prior selection. The comparison with other optimization methods will be the subject of our future work.

Renewable energy system (RES) deployment in primary schools across Algeria aligns seamlessly with the national drive to introduce sustainable electricity generation, specifically through photovoltaic (PV) sources. This study is dedicated to optimizing the installation costs of these systems in schools, a critical endeavor to overcome financial challenges, particularly in provinces where funding hurdles are prominent.

Identifying a local Algerian partner willing to embrace this initiative remains challenging despite earnest endeavors. As a potential avenue for resolution, exploring the international implementation of this program becomes crucial. Partnerships with Canadian organizations like Mitacs or Audace Technologies Inc., both actively supporting the research led by Dr. Abdellah Benallal, the primary author of this article, could serve as promising pathways to navigate the challenges and advance the adoption of renewable energy solutions in Algerian schools.

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Nomenclature

RES	Renewable Energy System
GHG	Greenhouse Gas
NPC	Net Present Cost
COE	Cost of Energy
TEF	Techno-Economic Feasibility
DGs	Diesel Generators
IRENA	International Renewable Energy Agency
AfDB	African Development Bank

IEA	International Energy Agency
PV	Photovoltaic
AI	Artificial Intelligence
DM	Demand Management
SMG	Smart Microgrids
WTs	Wind Turbines
Li-Ion	Lithium-Ion
TDC	Total Daily Consumption

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