International Journal of Smart Grid and Clean Energy

A Techno-economic feasibility study of a green energy initiative for a university campus

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Abstract

This paper proposes a novel methodology to redesign the power supply of a university campus characterized by a heavy reliance on diesel generators due to the grid unreliable power supply. The optimized design aims to phase out diesel generators and replace them with a hybrid clean energy system composed of photovoltaics and a battery storage system. A Genetic Algorithm approach is used to optimally size such a system, whereas the optimized energy dispatch is achieved through a rule-based energy management system. The study reveals that the implementation of clean technologies yields significant reduction in the system's operational cost. The impact of major parameters influencing the economics of the proposed system is assessed through a sensitivity analysis conducted over a 10-year period.

Keywords: Energy economics, genetic algorithm, microgrid optimal design, rule-based energy management system.

1. Introduction

Affordable and reliable electricity supply is essential in modern life. However, in many developing countries, power systems are normally characterized by scheduled blackouts and heavy reliance on diesel generators (DGs). Recently, the significant decrease in the capital cost of renewable energy systems, especially photovoltaics (PV) and battery storage systems (BSS) made the hybrid PV-BSS system more economically attractive.

Several recent publications focused on the importance of the hybridization of PV and BSS as a clean source energy alternative to fossil fuel-based electricity generation. The use of genetic algorithm (GA) was illustrated in references [1]-[15], where optimizations performed aimed to achieve both an optimal sizing of system components and an optimal energy management system (EMS) of the hybrid distributed energy resources. Another evolution based artificial intelligence algorithm using particle swarm optimization was described in [16, 17] and used to site a BSS aiming to minimize energy losses and mitigate voltage fluctuations due to the integration of hybrid renewable energy systems in distribution networks. Reference [18] proposed a multi-objective self-adaptive differential evolution algorithm to size PV, wind, diesel generators and BSS aiming to minimize loss of power probability and cost of electricity for a hybrid microgrid situated in Saudi Arabia. Minimizing investment cost while reducing BSS failure to support frequency regulation was illustrated in [19] through implementing an optimization model and a performance assessment algorithm for the sizing of a BSS considering not only the investment cost but also the inappropriate dispatch influence on batteries life span during operation. Reference [20] encouraged PV system owners to invest in BSS, using electron drift optimization algorithm, by demonstrating increased operational profits and improved power supply quality, through properly sizing and scheduling of BSS and smart inverter PV system. Modified brainstorm optimization was implemented in [21] on a moderately sized smart city in Japan. It aimed to minimize energy cost, shift electric power load and minimize CO_2 emissions. Reference [22] studied the influence of three different distributed generators (wind, PV, and small hydropower units) on the operation of a distribution network through implementing a two-stage GA based optimization aiming to reduce network's power losses and the unmet load cost.

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doi: 10.12720/sgce.10.3.203-214

This paper proposes the utilization of GA to determine the optimal sizes of PV and BSS under the influence of a rule-based EMS for university campus microgrid characterized by heavy reliance on on-site DGs due to an unreliable grid power supply. The paper is structured as follows: section 2 presents the problem formulation, section 3 provides the system modelling. The optimization approach is illustrated in section 4. Results are revealed in section 5, and conclusions are drawn in section 6.

2. Problem Formulation

The aim of this study is to redesign the power system of a university campus micro-grid, which suffers from scheduled grid blackout and hence relies heavily on DGs. The objective of the proposed power system is to determine the optimal PV and BSS capacities that minimize diesel generator energy dependency, grid's peak tariff purchased energy, and the overall system's cost of electricity, while maintaining 100% supply reliability without oversizing the system's components.

To achieve the above objectives, the problem at hand is modelled as a cost minimization function, as shown in (1):

$$\min \sum_{t=1}^{8760} \left\{ \frac{COE^{grid}(t)\times P^{grid}(t) + COE^{DG}(t)\times P^{DG}(t) + COE^{PV}\times P^{PV}(t) + COE^{BSS}\times P^{BSS}(t)}{P^{grid}(t)+P^{DG}(t)+P^{PV}(t)+P^{BSS}(t)} \right\} \tag{1}$$

where, COE^{grid}, COE^{DG}, COE^{PV} and COE^{BSS} are the energy cost in \$/kWh from grid, DG, PV system, and BSS respectively. P^{grid}, P^{DG}, P^{PV}, and P^{BSS} are the output power in kW from grid, DG, PV system, and BSS at any time t respectively.

3. System Modelling

This study targets the American University of Beirut (AUB) whose campus is currently supplied via two sources: the electric utility (EDL) and the on-site DG power plant. However, due to DGs' noise, pollution and diesel price fluctuations, this paper seeks to phase out DGs and replace them with a hybrid PV-BSS system. Fig. 1 illustrates the proposed system configuration controlled by an EMS, which decides on energy dispatch based on the daily input data (grid's tariff, load data, forecasted PV output, etc.…).

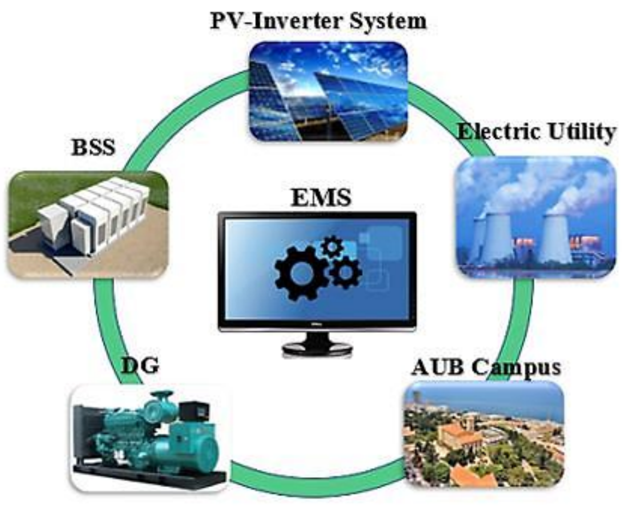

Fig. 1. Proposed system configuration

3.1. Electric utility model

Because of the lack of generation capacities, EDL supplies the AUB campus according to a daily rationing schedule. Fig. 2 illustrates the frequency of daily EDL outages based on its duration during the year of 2017.

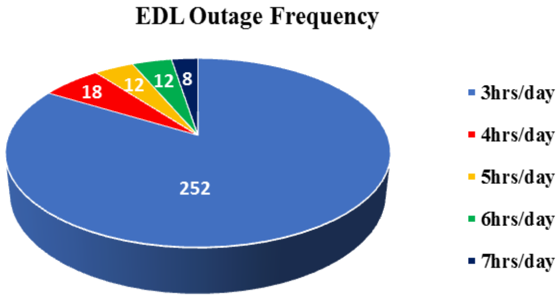

Fig. 2. EDL outages frequency in days during 2017

Additionally, AUB is subjected to a triple tariff system as depicted in Table 1.

Table 1.. EDLs tariff rates

Tariff Rate (₵/kWh)	5.3	7.3	21.3
Summer Season Hours	00:00-07:00 23:00-24:00	07:00-19:00 22:00-23:00	19:00-22:00
Winter Season Hours	00:00-07:00 23:00-24:00	07:00-17:00 21:00-23:00	17:00-21:00

3.2. AUB campus load

To enable system simulation, an hourly load profile of the AUB campus during the year of 2017 was used. Fig. 3 and Fig. 4 illustrate the average daily power demands during winter and summer season respectively. The average demand varies between 3MW and 7.2MW in winter, whereas in the summer season it varies between 3MW and 9.3MW. Occasionally, the peak demand reaches 12MW.

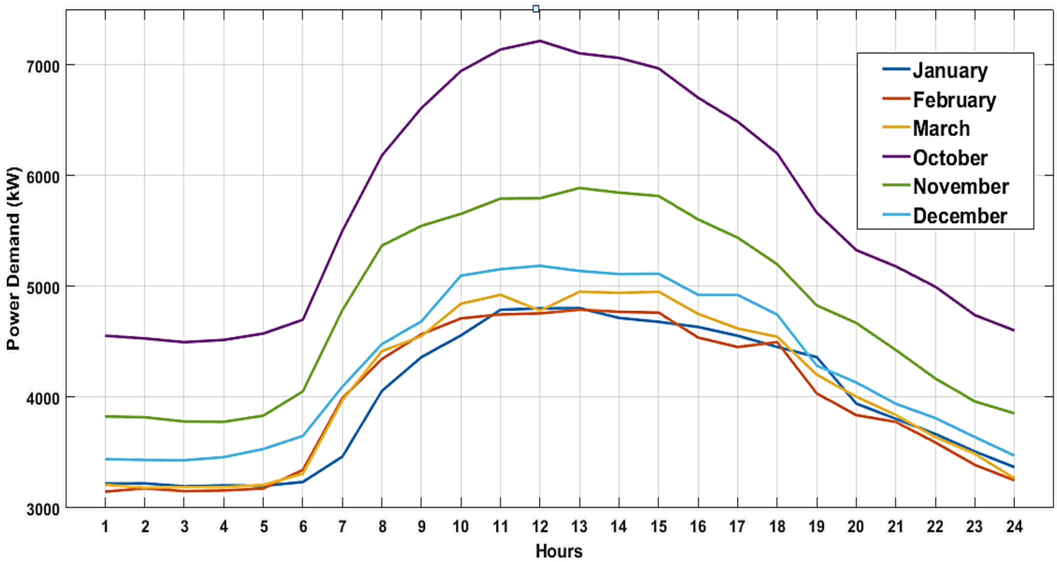

Fig. 3. Daily average demand during winter

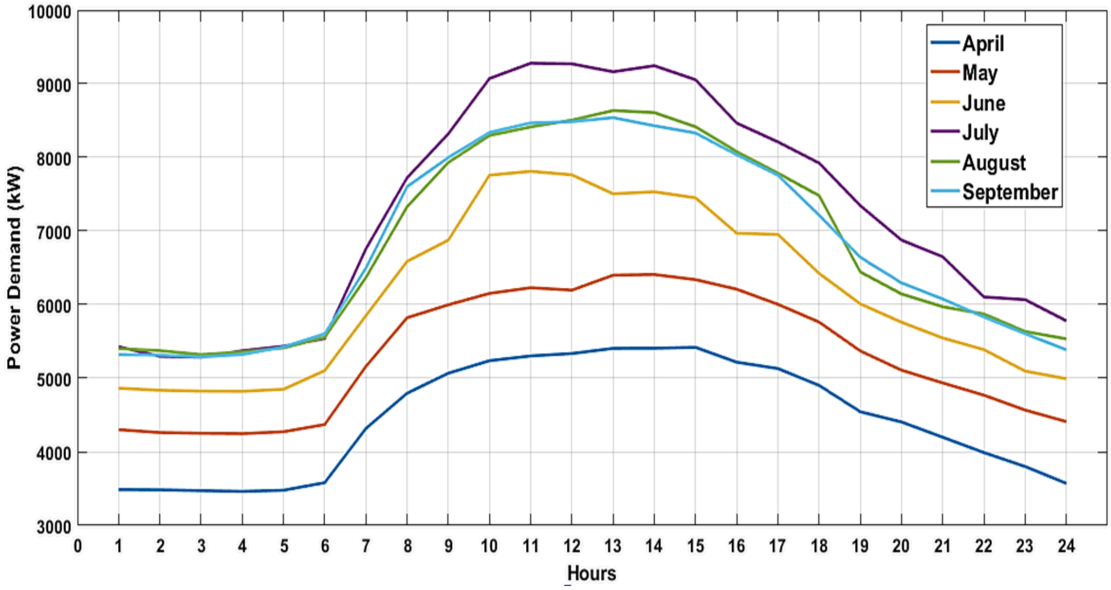

Fig. 4. Daily average demand during summer

3.3. Diesel generator model

AUB has its own installed DG plant consisting of 13 DGs of different sizes, having a total generation capacity of 15.3MW. The COE of the DGs is calculated as shown in (2) to (5)

$$COE^{DG} = \frac{CC^{DG} \times CRF(i,N) + O\&M^{DG} + \sum_{t=1}^{8760} DC(t)}{\sum_{t=1}^{8760} P^{DG}(t)} \tag{2}$$

$$CRF(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1} \tag{3}$$

$$DC(t) = \gamma(t) \times FC(t) \tag{4}$$

$$FC(t) = \alpha P^{DG}(t) + \beta P^{DG}_{rated} \tag{5}$$

Where, CC^{DG} is the DG capital cost, CRF is capital recovery factor at an interest rate *i* and period *N*, $O\&M^{DG}$ is the DG annual operation and maintenance cost, DC(t) is the diesel fuel cost in ($), $\gamma(t)$ is the diesel fuel price ($/litre), FC(t) is the diesel generator fuel consumption (litre), $P^{DG}(t)$ is the diesel generator output power, P^{DG}_{rated} is the diesel generator rated capacity, and α and β are fuel consumption coefficients.

3.4. Photovoltaic system model

The PV output power is calculated using (6) and (7).

$$P_M^{PV}(t) = PV_M^{out}(t) \times \eta_{inv} \tag{6}$$

$$PV_M^{out}(t) = FF(t) \times I_{sc}(t) \times V_{OC}(t) \tag{7}$$

where, P^{PV}_M is the PV module forecasted AC power (kW), PV^{out}_M is the forecasted PV module DC output power (kW), η_{inv} is the PV system's inverter efficiency. FF, I_{sc}, and V_{OC} are the PV module fill factor, short circuit current (A) and open circuit voltage (V) respectively at any time t.

Data representing an hourly measurement of solar irradiance and ambient temperature for the year of 2017 were used to calculate the forecasted PV module output power. Readers may refer to [5] for the full PV system model used. Fig. 5 shows the calculated PV annual output power profile.

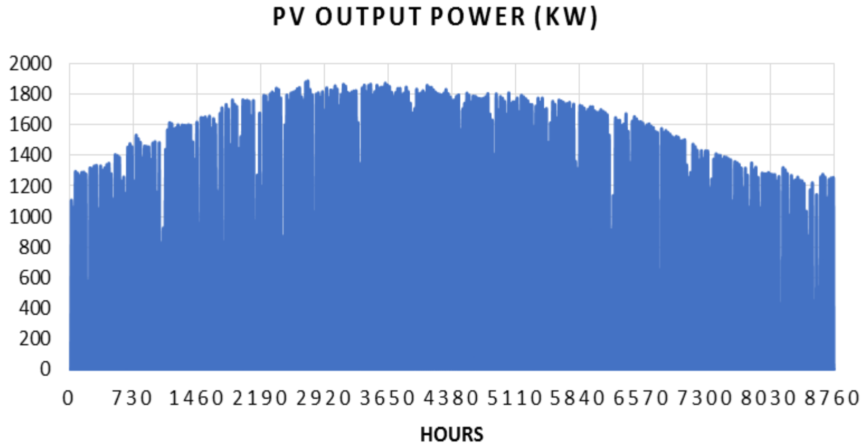

Fig. 5. PV capacity output power profile

The average capital cost for several PV system capacities along with their annual maintenance cost were provided by several suppliers. The capital cost of the system to be installed is assumed to be fully covered through a bank loan with a subsidized 2.5% interest rate for a 10-year period. Using such information, the annuities and COE as a function of PV system capacity are formulated as shown in (8) and (9).

$$AP^{PV} = CRF(i,N) \times CC^{PV} \tag{8}$$

$$COE^{PV} = \frac{AP^{PV} + O\&M^{PV}}{\sum_{t=1}^{8760} P^{PV}} \tag{9}$$

where AP^{PV} is the PV system loan's annual payment, CC^{PV} and $O\&M^{PV}$ are the PV system's capital cost and annual operation and maintenance cost respectively.

3.5. Battery storage system model

The BSS model is given in (10) and (11).

$$P^{BSS}(t) = \begin{cases} \dfrac{P_{DC}^{BSS}(t)}{\eta_{Batt}} \rightarrow \text{charging} \\ P_{DC}^{BSS}(t) \times \eta_{Batt} \rightarrow \text{discharging} \end{cases} \tag{10}$$

$$SOC(t) = \left\{ \begin{array}{l} SOC(t-\Delta t)(1-a) + \dfrac{P_{DC}^{BSS}(t)}{C^{BSS} \times V^{BSS} \times SOH(t)} \rightarrow \text{charging} \\ SOC(t-\Delta t)(1-a) + \dfrac{P_{DC}^{BSS}(t)}{C^{BSS} \times V^{BSS} \times SOH(t)} \rightarrow \text{discharging} \end{array} \right\} \tag{11}$$

where, P^{BSS}_{DC} is the DC charging-discharging rate of the battery in an interval Δt. P^{BSS} is the AC power charged or discharged from the battery with a battery-inverter efficiency η_{Batt}. SOC is the state of charge of the battery, C^{BSS} is the nominal battery capacity (Ah), V is the battery nominal voltage (V), "a" is the self-discharging factor, and SOH is the battery state of health.

In order to account for the impact of energy discharge on the battery capacity, segmented linear function describing SOH as a function of the cumulative discharged energy during a 10-year period was formulated based on the data shown in Fig.6.

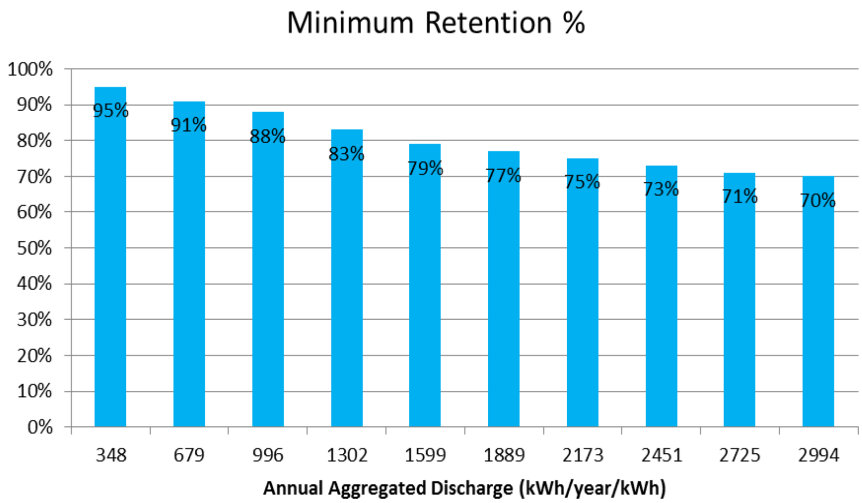

Fig. 6. Battery model annual retention regime as a function of cumulative annual discharged power

Like the process followed for the PV system, the annual payment and COE as a function of BSS installed capacity are computed using (12) and (13).

$$AP^{BSS} = CRF(i,N) \times CC^{BSS} \tag{12}$$

$$COE^{BSS} = \frac{AP^{BSS} + O\&M^{BSS} + \sum_{t=1}^{8760} P_{char}^{BSS}(t) \times \min COE^{grid}}{\sum_{t=1}^{8760} P_{disch}^{BSS}(t)} \tag{13}$$

where AP^{BSS}, CC^{BSS}, and $O\&M^{BSS}$ are the BSS's loan annual payment, capital cost and annual operation and maintenance cost respectively. P^{BSS}_{char} and P^{BSS}_{disch} are the BSS charging and discharging AC power respectively, and min COE^{grid} is the minimum grid tariff rate during which the charging process occurs.

4. Optimization Approach

Optimization is based on the combined utilization of GA as a sizing tool and a rule-based EMS acting as a fitness function to the optimization problem. For each PV and BSS capacity generated by GA, the rule-based EMS is run for the entire year period, considering seasonal load and climate variations, grid's varying tariffs, BSS's SOC and SOH while assuring 100% supply reliability. After calculating the entire year power profile, the objective function illustrated in (1) is computed, assessed and then ranked based on its fitness value. Since GA is an evolutionary based heuristic approach, this process is performed several times, such that only elite (best fit) individuals are made to survive and form the next generation. Some mutations and crossover will be performed on some of the parent individuals (best fit capacities) to create a new generation, equal in size to the previous one, and test its individual performances. Such loop is repeated until a pre-set stopping criterion is reached.

Fig. 7 illustrates the optimization algorithm conducted. For each generated PV and BSS capacity, the EMS starts by checking if EDL is ON or OFF, on an hourly basis. If EDL is OFF, PV and BSS are used as primary sources of energy, and if there is any generation deficiency, DGs are then used. However, if grid is ON, the EMS checks for peak tariff hours. During Off peak hours, the algorithm chooses to: (1) satisfy the demand from PV and EDL and (2) charge the BSS during night tariffs. Whereas, during peak

hours, if grid was OFF during that day, the algorithm will supply the load from PV generated energy and then from the remaining BSS energy. If the load is still not satisfied, grid energy will bridge the gap. While, if grid wasn't OFF during that day, PV and grid purchased energy are used to supply the demand leaving the batteries for the next blackout hours.
The constraints in this optimization problem are given in equations (14) to (24)

$$0 \leq PV^{Cap} \leq 2,400kW \tag{14}$$

$$6,000 \leq P^{BSS}_{Cap} \leq 22,000kW \tag{15}$$

$$P^{PV}(t) = PV^{Cap} \times \frac{PV^{out}_{M}(t)}{PV^{M}_{r}} \times \eta_{inv} \tag{16}$$

$$E^{BSS}_{Cap} = P^{BSS}_{Cap} \times 2.965 \tag{17}$$

$$E^{BSS}_{Max-Daily} = E^{BSS}_{Cap} \times \frac{348}{365} \rightarrow \text{1st Year} \tag{18}$$

$$\sum_{t=1}^{24} P^{BSS}_{Disch,DC} \leq E^{BSS}_{Max-Daily} \tag{19}$$

$$SOC_{\min} \leq SOC \leq SOC_{\max} \tag{20}$$

$$0 \leq P^{grid} \leq \infty \tag{21}$$

$$0 \leq P^{DG} \leq P^{DG}_{Max} \tag{22}$$

$$0 \leq P^{BSS} \leq P^{BSS}_{Max} \tag{23}$$

$$P^{grid}(t) + P^{DG}(t) + P^{BSS}(t) + P^{PV}(t) = P^{D}(t) \tag{24}$$

Where, PV^{Cap}, PV^{out}_{M}, and PV^{M}_{r} are PV system capacity, PV module output and PV module rated power (in kW) respectively. E^{BSS}_{Cap}, $E^{BSS}_{Max\text{-}Daily}$, and $P^{BSS}_{Disch,DC}$ are BSS's rated capacity (BSS is designed to supply rated power P^{BSS}_{Cap} for approximately 3 hours), maximum allowable daily discharged energy (kWh), and the BSS's DC discharged power (in kW) respectively. Whereas, P^{D} is the power demand (in kW).

5. Simulation Results & Sensitivity Analysis

5.1. Sizing and time domain power flow analysis

Applying the proposed methodology, the optimal PV system and BSS along with the project financial data are provided in Table II. The optimized hybrid system was run for a 10-year period under the control of the aforementioned EMS and the results are summarized in Table III. The installation of 2,400 kW PV and 9,000 kW-26,685 kWh BSS was able to shrink DG energy dependency to 0.78% of the total generated energy during the first year and guarantee that such dependency won't exceed 1.51% after 10 years.

To assess the financial merits of the proposed system, the current system's financial indicators were computed as shown in Table IV. Assuming that EDL's tariff and DGs' power output remains constant, and only the DGs' fuel cost increases subsequently by 1% per year due to yearly fuel price escalation, the COE is projected to increase to 14.4 ¢/kWh in year 10.

Table V illustrates the proposed system's financial indicators. As can be seen, the optimized system reduced DG annual operating cost from 53.7% during the 1st year, to a maximum of 3.7% at the 10th year, cut down overall annual cost, yielding an annual average savings of \$1.23M, reduced overall system's COE from 0.137\$/kWh to 0.092\$/kWh in the 1st year and from 0.144\$/kWh to 0.102\$/kWh in the 10th year, and guarantee a positive cash flow at the 6th year of putting such a system into operation.

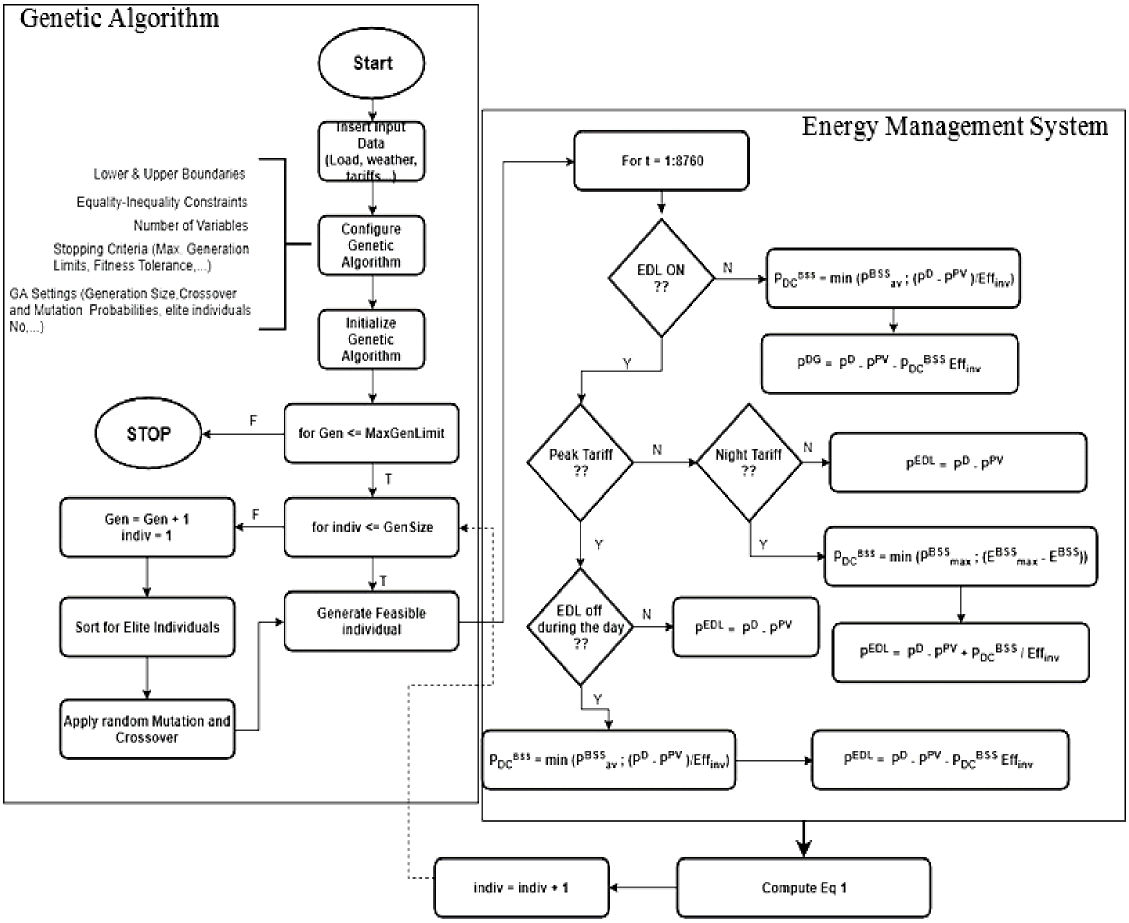

Fig. 7. Optimization approach flow chart

Table 2. Optimal PV-BSS capacity and financial data

Optimal PV Capacity (kW)	2,400 kW
Optimal BESS Capacity (kW - kWh)	9,000 kW - 26,685 kWh
PV Capital Cost (\$)	2,098,284 \$
BESS Capital Cost (\$)	11,046,430 \$
PV O&M Cost (\$/year)	20,983 \$
BESS O&M Cost (\$/year)	36,945 \$
Interest Rate (%)	2.5%
Loan Period (years)	10 years
PV Annual Payment (\$)	260,730 \$
BESS Annual Payment (\$)	1,299,096 \$

Table 3. Time domain power flow energy outlook

	Year 1	Year 2	…	Year 10
EDL (kWh)	43,015,621	42,990,680	…	42,440,087
DG (kWh)	430,314	440,522	…	803,283
BESS Disch (kWh)	7,926,340	7,790,533	…	6,056,617
BESS Char (kWh)	8,785,747	8,635,210	…	6,713,462
PV (kWh)	3,957,422	3,957,422	…	3,957,422
Load (kWh)	46,543,950	46,543,950	…	46,543,950
Generation (kWh)	55,329,697	55,179,159	…	53,257,410
Demand (kWh)	55,329,697	55,179,159	…	53,257,410
DG Share (%)	0.78%	0.80%	…	1.51%

Table 4. Existing system's energy and financial indicators

	Year 1	Year 2	…	Year 10
Load (kWh)	46,543,950	46,543,950	…	46,543,950
EDL (kWh)	30,208,624	30,208,624	…	30,208,624
DG (kWh)	16,335,326	16,335,326	…	16,335,326
DG Share (%)	35%	35%	…	35%
EDL Energy Cost ($)	2,953,308	2,953,308	…	2,953,308
DG Energy Cost ($)	3,430,418	3,464,723	…	3,751,798
Overall Cost ($)	6,383,727	6,418,031	…	6,705,107
COE ($/kWh)	0.137	0.138	…	0.144

Table 5. Yearly financial outcome of the proposed system

	Year 1	Year 2	…	Year 10
EDL Cost ($)	3,500,223	3,518,992	…	3,709,013
DG Cost ($)	107,579	110,131	…	200,821
PV Cost ($)	260,730	260,730	…	260,730
BESS Cost ($)	1,299,096	1,299,096	…	1,299,096
Total Cost ($)	5,150,416	5,172,254	…	5,453,332
COE ($/kWh)	0.092	0.093	…	0.102
Savings ($)	1,233,311	1,245,777	…	1,251,774

5.2. Sensitivity analysis

Figs. 8, 9, and 10 represent the impact of interest rate (IR %) variations, EDL tariffs escalation, and diesel fuel price escalation on the yearly savings respectively. The IR can significantly affect the project's financial merits, dropping the annual savings to an average of $0.595M as the interest rate increases to 10% as seen from Fig. 8. As for the system's payback period (PP), an increase in interest rate from 2% to 10% will cause the PP to increase from 6 to 8 years. Similarly, as depicted in Fig. 9, the increase in EDL tariffs reduces the system's attractiveness. For instance, a 40% increase in EDL's tariff rates would reduce average annual savings to $0.964M. On the contrary, as depicted from Fig. 10, the increase in diesel fuel price makes the optimized system more economically attractive and profitable.

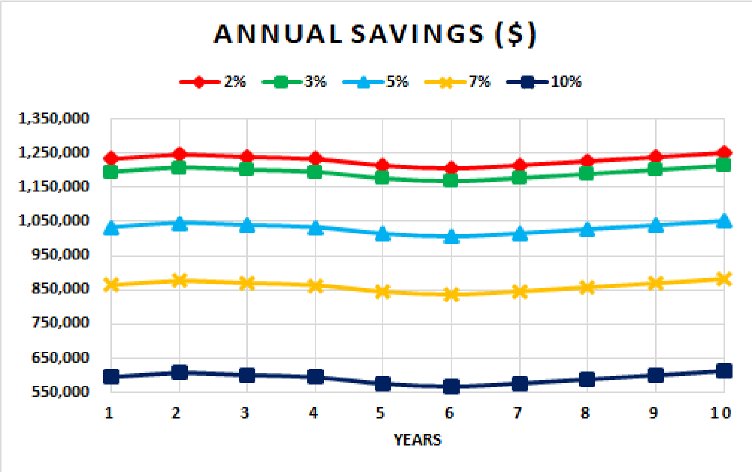

Fig. 8. Yearly savings at different interest rates

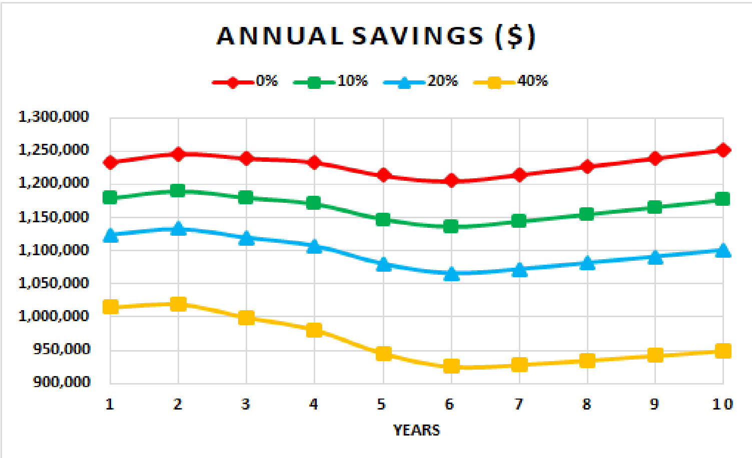

Fig. 9. Yearly savings at different EDL tariff escalation rates

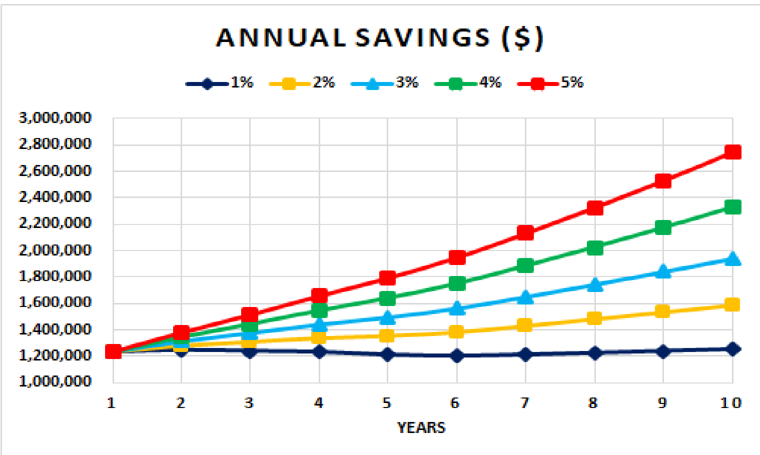

Fig. 10. Yearly savings at different fuel price escalation rates

6. Conclusion

This paper had described an optimization approach based on the combined utilization of genetic algorithm (GA) and a rule-based EMS to determine the optimal photovoltaic (PV) and battery storage system (BSS) capacities that would minimize diesel dependency and grid's purchased peak tariff energy. The proposed approach was tested on a university campus load characterized by repetitive grid blackouts and heavy reliance on diesel generators.

Testing the optimized system's performance for an entire 10-year period revealed that the added capacities along with the EMS developed, would almost completely eliminate the diesel generators, yield \$1.23M of average annual savings and reduce significantly the system's overall COE starting from the first year. Upon studying the system's economic sensitivity to possible input variations, the analysis revealed that the project would continue to be profitable under all varying conditions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Riad Chedid: Conceptualization, Methodology, Supervision, Review & Editing.
Ahmad Sawwas: Writing original draft, Investigation, Formal analysis, Software.

Acknowledgements

The authors acknowledge the support provided by the Maroun Semaan Faculty of Engineering and Architecture at the American University of Beirut.

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