Research Article

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Renewable Energy Integration on a High Inflation Economic Scenario by Means of Firework Algorithm, Genetic Algorithm and Monte Carlo Simulation

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Abstract

This paper presents a solution to the Renewable Energy Integration Problem (REIP) by finding the Optimal Configuration of components required in a hybrid microgrid located in Kuwait, such that the cost of energy (COE) is minimized when considering several components such as: solar panels, wind turbines, electric batteries, converters, inverters, diesel generators and connection to the power grid. The optimal configuration is found by evaluating the interaction and effects of several combinations of components via Monte-Carlo simulation, and such configurations are in turn optimized by means of 2 alternative stochastic algorithms: The Genetic Algorithm and the Fireworks Algorithm. The two approaches are compared, concluding that the Fireworks Algorithm provides more variety of configurations along the iterations before reaching convergence. The evaluation by Monte-Carlo simulation is calculated, by means of Present Worth (PW) with a minimum attractive rate of return (MARR) set to 7 percent to represent a high inflation rate-scenario, concluding that both methods can be safely used to optimize the design of hybrid micro-grids under high economical stress.

Keywords: *Genetic Algorithm, Fireworks Algorithm, Monte Carlo Simulation, Renewable Energy, Optimization, Hybrid Microgrid, Inflation*

1. Introduction

Electricity consumption has been increasing worldwide during the last 50 years (IEA, 2021). And most of the electricity currently being generated is from fossil fuel-based methods such as coal, gas, nuclear and oil, particularly on OECD countries (IEA,2021) as shown in figure 1 below.

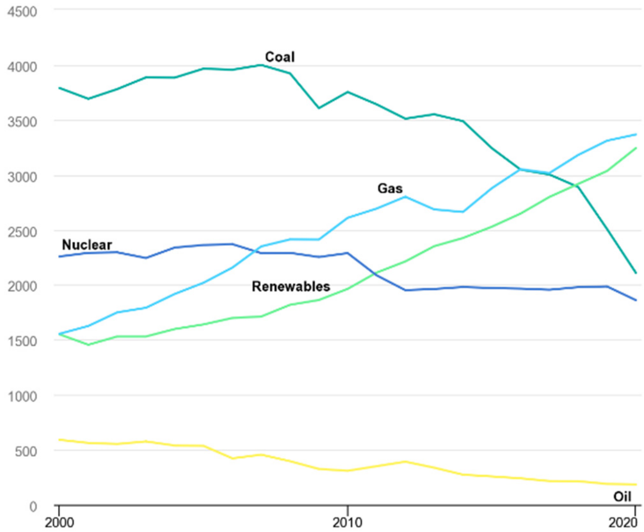

Figure 1: Electricity Generation by source, OECD, 2000-2020. From IEA, 2021.

This calls for our attention, as it is also noted that fossil fuels are depleting word wide, as shown in figure 2 below from EIA, International Energy Statistics 2022, showing data from China's coal consumption and production.

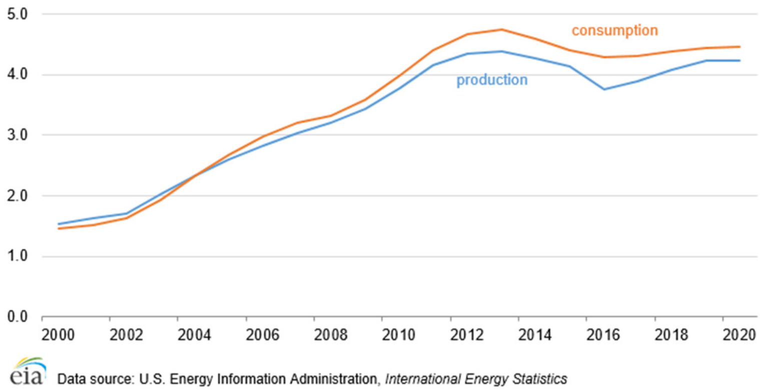

Figure 2: China's coal supply and demand, 2000-2020. International Energy Statistics.

The coal statistics from China shown above could be considered as a key performance metric to understand the overall status of fossil fuels relationship to electricity generation, since coal has been the main source for electricity production worldwide for many years as seen in figure 1, just recently overtaken by natural gas. Moreover, the utilization of such resource could be monitored by focusing on China as it is currently ranked as the country with the highest electricity consumption in the planet, as shown in Figure 3 below.

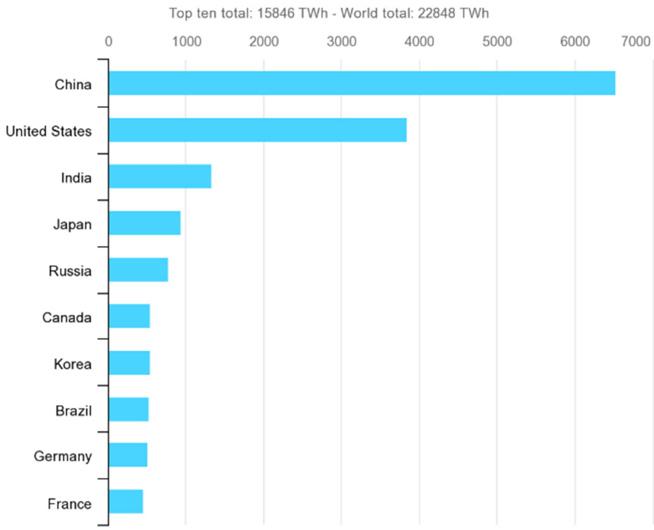

Figure 3: Top 10 electricity consuming countries, EIA, 2019.

It is also important to note that when performing the forecast of available resources into the future, it is crucial to consider the potential increases on the rates of demand and production that may happen, such that the overall consumption of the available resources could also most likely accelerate, hence decreasing the lifetime of the available world reserves of such resources.

According to the mathematical model presented by Shafiee. S. & Topal. E. in their 2009 paper in which they calculate the fuel reserves depletion times, there is oil for approximately 35 more years from their time of publication, coal for 107 years and gas for 37 years, which accounting for the current date makes it a correction for 21 years left of oil, 93 years for coal depletion and 23 years for gas depletion

Additionally, these findings appear to confirm the theoretical model presented by Hubbert in 1956, which has been widely used as a reference and starting point to predict the availability of future finite resources, including fossil fuels.

Problem Statement

From these discussions it can be inferred that there is a need and urgency to incorporate the utilization of alternative sources for electricity generation that do not rely on fossil fuels. This means that the increase of renewable energy development & utilization is a reasonable objective to be pursued by the different engineering organizations, moreover including high inflation rates to account for future possible economic scenarios.

2. Background

2.1 The hybrid state of electric networks

Switching from fossil fuels utilization to renewable energy sources for electricity production calls for an intermediate step: the hybrid electric networks. A hybrid electric network is understood to be an electrical system that is including components for electricity creation that are both fossil-fuel based as well as renewable source-based. Moreover, it is important to distinguish between the power-grid and the micro-grid.

2.2 Power grid and micro grid

Electricity is created, delivered, and consumed by the end-users in essentially 3 stages: these 3 stages together can be understood to be the power grid.

Production Phase: The 1st phase is the creation of electricity in massive amounts in power plants, by utilizing different mechanisms and sources which can be fossil fuel based such as nuclear, coal, natural gas, oil, or they can be renewable source based such as solar, wind, hydro-power, etc.

Transmission Phase: The 2nd phase is the transmission of such electricity via transmission network lines, to carry the electricity from the power plants into the cities and towns where it will be consumed by the end users. Usually, transmission lines have very high voltage to reduce the losses incurred by the long distances.

Distribution Phase: The 3rd phase is the distribution phase, which typically occurs inside cities and towns, and in which the voltage from the transmission phase is decreased for safety purposes.

Microgrid: Once the electricity reaches the private property, typically a clear division is made to distinguish the power grid from the micro grid, at the electric meter. From the electric meter onwards, the electric network is private property, and responsibility of the end-user (property owner) to safely operate, maintain, and to keep in concordance with any law requirement or standard, according to their own country and legal system. This final private property section of the electric network is known as the microgrid.

Connected Microgrids and Islanded Microgrids:

In most urban areas, the microgrids are connected to the power-grid, and as such, the end-user can purchase the electricity directly from the electric company who is producing it in their distanced power plants as described previously. In such cases, the electric meter at the border/connection between the micro-grid and power-grid is utilized to measure the amount of electricity that is entering the micro-grid, and the end-user is correspondingly charged an agreed monetary amount defined by the contract between the end-user and the electric provider.

2.3 Problem Formulation

The configuration of a hybrid microgrid is understood to be the list of components that are contributing to the introduction of electricity into the system, as well as the list of components that are consuming the electricity from the system.

The electricity source components considered in our formulation are: Solar Panels, Wind Turbines, Diesel Generators, Electric Batteries, Converters, Inverters and Rectifiers.

Additionally, the list of components that are consuming electricity is compiled in a single generalizing term, which we labelled total demand at time t: $TD(t)$ and it represents the total summation of electricity being consumed in the microgrid at any point in time by adding all electric sinks such as lightbulbs, ventilation systems, screens, etc.

From the above we can present the formulation of our objective function: the total cost function. The cost of the system can be understood as the summation of all capital (initial) costs, operation and maintenance costs and any replacement costs that may occur during the operation of the microgrid.

Each component will generate a cost when is purchased, a cost when is operated and maintained in a yearly basis, and another cost when the component is replaced after it has decayed due to its utilization. We note that the cost of replacement is the cost of purchase minus the salvage value obtained from selling the old version of the item being replaced at the end of its useful life.

The objective function can be described as follows:

$Min(TC) = TC_{CC} + TC_{OMC} + TC_{RC}$

Where:

TC = Total Cost

TC_{CC} = Total Capital Costs

TC_{OMC} = Total Operation and Maintenance Costs

TC_{RC} = Total Replacement Costs

The cost formulation presented above does not include any revenue, as it represents a micro-grid that is **not selling** any electricity back to the power grid.

The Total Capital Costs term from equation 1 above are in turn the summation of the individual capital costs incurred by each of the components included in the micro-grid configuration. This means that the following equation can be used to describe such total capital costs:

$$TC_{CC} = \sum_{j=1}^{m}\sum_{i=1}^{n} CC_{PV_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} CC_{WT_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} CC_{DG_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} CC_{EB_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} CC_{K_{i,j}}$$

Where:

TC_{CC} = Total Capital Costs

$CC_{PV_{i,j}}$ = Capital Cost of Photovoltaic (PV) system *i*, where *i* is defined from 1 to *n* to depict the number of components of size *j* that are included in the microgrid, and the number of sizes *j* can go from category 1 to category *m*.

$CC_{WT_{i,j}}$ = Capital Cost of Wind-Turbines (WT) in the same fashion as above.

$CC_{DG_{i,j}}$ = Capital Cost of Diesel Generators (DG) in a similar approach.

$CC_{EB_{i,j}}$ = Capital Cost of Electric Batteries (BT) following the same labelling logic as above.

$CC_{K_{i,j}}$ = Capital Cost of Electric Converters (K) with the same approach as above. It is important to note that converters can be either converters, inverters and/or rectifiers as needed, and treated as a single category of component.

The Capital Costs mentioned above include purchase costs, transportation costs to the site, installation costs as well as any other licensing, permit or taxation fee that must be paid prior to the operation of each component. Moreover, in order to consider the inflation rate, it is prudent to find the equivalent present values of all amounts that are not occurring in the present year (W. Sullivan et al, 2014). We can do this by calculating the Present Equivalent for the yearly costs i.e. operation & maintenance costs, for which the functional symbol (P/A, i%, n) is used as recommended by Sullivan et al in chapter 4 of their book.

As such, the expression used is the following:

$$TC_{OMC} = (P/A, f, N)\left(\sum_{j=1}^{m}\sum_{i=1}^{n} OMC_{PV_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} OMC_{WT_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} OMC_{DG_{i,j}} + \sum_{j=1}^{m}\sum_{i=1}^{n} OMC_{EB_{ij}} + \sum_{j=1}^{m}\sum_{i=1}^{n} OMC_{K_{ij}}\right)$$

Where:

TC_{OMC} = Total Operation and Maintenance Costs as present equivalent from their corresponding annual series.

$OMC_{PV_{i,j}}$ = is the yearly Operating and Maintenance Costs associated with photovoltaic component *i*, where *i* is defined from 1 to *n* to depict the number of photovoltaic components of size *j* that are included in the microgrid, and the number of sizes *j* can from category 1 to category m.

$OMC_{WT_{i,j}}$ = is the yearly Operating and Maintenance Costs associated with wind-turbine *i*, following a similar nomenclature as above.

$OMC_{DG_{i,j}}$ = is the yearly Operating and Maintenance Costs associated with the diesel generator component *i*, using the same approach as above.

$OMC_{EB_{i,j}}$ = is the yearly Operating and Maintenance Costs associated with electric battery component *i*, in the same fashion as the others.

$OMC_{K_{i,j}}$ = is the yearly Operating and Maintenance Costs associated with electric converter, rectifier and/or inverter component *i*, in a similar categorizing approach.

$(P/A, f, N)_{i,j}$ = is the functional symbol of 'present given annual' equivalency, using standard engineering economics notation in order to depict the formula that finds the monetary present value such that it is equivalent to the total summation of a series of cash flows that are occurring on a yearly basis and are subjected to an effective compound interest rate. The represented formula by such functional symbol is the following:

$$(P/A, f, N) = \frac{(1+f)^N - 1}{f(1+f)^N}$$

Where the term f represents the inflation rate, expressed as a compounded interest rate.

Following a similar logic, we express replacement cost as a variety of capital recovery as follows:

$$RC_{PV_{i,j}} = [CC_{PV_{ij}}(A/P, f, N_{PV_{ij}})$$
$$-SV_{PV_{ij}}\left(A/F, f, N_{PV_{ij}}\right)](P/A, f, N)$$

Equation 5 above is the replacement cost of solar panel i, of size category j, expressed by the equivalent amount in present time. The functional symbol represents the following relationship:

$$(A/F, f, N_{PV_{ij}}) = \left(\frac{f}{(1+f)^{N_{PV_{ij}}} - 1}\right)$$

Where:

f = is the inflation rate stated in the same fashion as in equation 4.

$N_{PV_{ij}}$ = is the lifetime in years of the solar panel component i, for size category j.

And fig. 4 below presents an example of a behavior when we assume a component lifetime of 3 years (for explanatory purposes only), and repeat the replacement process continuously:

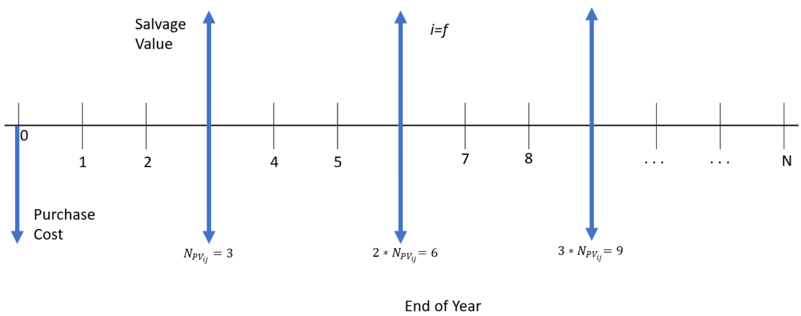

Figure 4: Cashflow diagram of a component being replaced at the end of its lifetime $N_{PV_{ij}} = 3$, for illustrative purposes.

From the diagram above, it is clear that that each cycle will produce a similar annual series as depicted in the red cashflows shown in fig. 5 below:

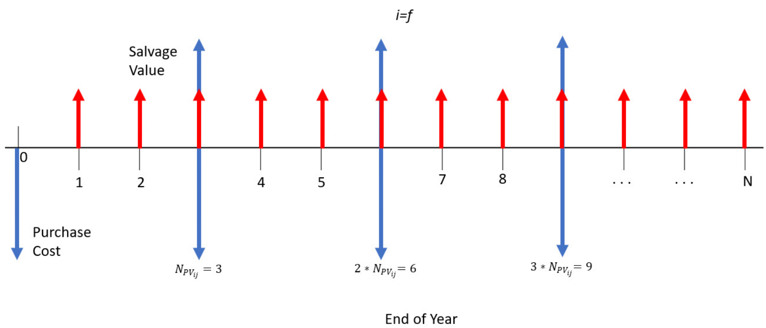

Figure 5: Cashflow diagram with annual equivalency of purchase cost – salvage value.

Following the logic shown above, it is now possible to find the present equivalency for all the uniform series of the system as:

$RC_{PV} = \sum_{j=1}^{m}\sum_{i=1}^{n}[CC_{PV_{ij}}(A/P,f,N_{PV_{ij}}) - V_{PV_{ij}}\left(A/F,f,N_{PV_{ij}}\right)](P/A,f,N)]$

Where:

RC_{PV} = is the total replacement cost for all photovoltaic components

$CC_{PV_{ij}}$ = is the capital cost associated to purchasing, transporting and installing each photovoltaic component *i* of category size *j* into the microgrid every time is needed as expected at the end of the lifetime $N_{PV_{ij}}$ for each photovoltaic component.

f = is the inflation rate in the same fashion as in equation 4.

$N_{PV_{ij}}$ = is the lifetime in years of the solar panel component *i*, for size category *j*.

N = is the **total project intended lifetime**, independent of the lifetime of each of the individual components considered in the microgrid.

As such, it is now evident that the equation for the replacement cost for wind turbines can take the following expression:

$RC_{WT} = \sum_{j=1}^{m}\sum_{i=1}^{n}[CC_{WT_{ij}}(A/P,f,N_{WT_{ij}}) - V_{WT_{ij}}\left(A/F,f,N_{WT_{ij}}\right)](P/A,f,N)]$

Where:

RC_{WT} = Total replacement costs for all wind turbines.

$CC_{WT_{ij}}$ = Are the capital cost of each wind turbine.

$N_{WT_{ij}}$ = Lifetime (in years) of each wind turbine.

And for diesel generators it becomes:

$RC_{DG} = \sum_{j=1}^{m}\sum_{i=1}^{n}[CC_{DG_{ij}}(A/P,f,N_{DG_{ij}}) - V_{DG_{ij}}\left(A/F,f,N_{DG_{ij}}\right)](P/A,f,N)]$

Where:

RC_{DG} = Total replacement costs for all diesel generators.

$CC_{DG_{ij}}$ = Are the capital costs of each diesel generator.

$N_{DG_{ij}}$ = Lifetime (in years) of each diesel generator.

For converters, rectifiers and inverters the expression is:

$RC_{K} = \sum_{j=1}^{m}\sum_{i=1}^{n}[CC_{K_{ij}}(A/P,f,N_{K_{ij}}) - V_{K_{ij}}\left(A/F,f,N_{K_{ij}}\right)](P/A,f,N)]$

(10)

Where:

RC_K = Total replacement costs for all rectifiers/converters/inverters.

$CC_{K_{ij}}$ = Capital costs of each converter, rectifier and inverter

$N_{K_{ij}}$ = Lifetime (in years) of each converter, rectifier or inverter

Finally, we can complete our model for replacement costs:

$TC_{RC} = RC_{PV_{i,j}} + RC_{WT_{i,j}} + RC_{DG_{i,j}} + RC_{K_{i,j}}$

Finalizing the objective function definitions for finding total cost, however, there must be constraints pertaining to the production of electricity, shown next.

Constraints

Each configuration must provide enough electricity to avoid blackouts. As such, we calculate electric balance to ensure the electricity provided is at least equal or greater than zero for all time steps.

$B(t) = TS(t) - TD(t)$

Where:

$B(t)$ = is the total electric balance at time t

$TS(t)$ = is the total electric supply at time t

$TD(t)$ = is the total electric demand at time t

And such value must be positive or zero at all times:

$B(t) \geq 0, \forall t$

Moreover, we can also note that the total electric supply of the system is equal to the summation of the individual contributions for all components supplying electricity to the microgrid at time t:

$$TS(t) = \sum_{j=1}^{m}\sum_{i=1}^{n} S(t)_{PV_{ij}} + \sum_{j=1}^{m}\sum_{i=1}^{n} S(t)_{WT_{ij}} + \sum_{j=1}^{m}\sum_{i=1}^{n} S(t)_{DG_{ij}} + \sum_{j=1}^{m}\sum_{i=1}^{n} S(t)_{EB_{ij}}$$

Where:

$S(t)_{PV_{ij}}$ = is the electric supply of the photovoltaic component i from size category j at the specific time t.

$S(t)_{WT_{ij}}$ = electric supply of each wind turbine at time t.

$S(t)_{DG_{ij}}$ = electric supply of each diesel generator at time t.

$S(t)_{EB_{ij}}$ = electric supply of electric battery at time t

To include the consideration that each component produces electricity differently, we use the following models.

2.4 Solar Panel Model

The solar panel model used is the one proposed by Lambert et al.

$$S(t)_{PV_{ij}} = Y_{PV_{ij}} f_{PV_{ij}} \left(\frac{G_T}{G_{T,STC}}\right)\left[1 + \propto_{P_{ij}} \left(T_{C_{ij}} - T_{C,STC}\right)\right]$$

Where

$Y_{PV_{ij}}$ = is the rated capacity in kW of the PV array i of size category j.

$f_{PV_{ij}}$ = is the PV derating factor of the solar panel.

G_T = is the solar radiation in the current time step, in kW/m^2.

$G_{T,STC}$ = solar radiation at standard test conditions.

$\alpha_{P_{ij}}$ = the temperature coefficient of power for the solar panel.

T_C = is the temperature at the current time step in °C.

$T_{C,STC}$ = temperature at standard test conditions, set to 25°C.

The values from above can be obtained from the component supplier except of T_C and G_T, which must be obtained from environmental factors pertaining to the location of the microgrid.

2.5 Wind Turbine Model

The model of the wind turbine utilized is the following, from Lambert et al.

$$S(t)_{WT_{ij}} = \frac{1}{2}\left[\left(\frac{P_o\left(1-\frac{Lh}{T_o}\right)^{\frac{gM}{RL}}}{R_{da}(T_o-Lh)}\right) + 6.1078 * \emptyset * \left(\frac{\left(10^{\frac{7.5T-2048.625}{T-35.85}}\right)}{R_V(T_o-Lh)}\right) * AC_p * U_r\left(\frac{t}{Z_r}\right)^{\alpha} N_g e^{-K_g t} * N_b^{-K_b t}\right]$$

Where:

P_o = standard Atmospheric pressure at sea level = 101,325 Pa.

L = is the Temperature Lapse Rate = 0.0065 $\frac{K}{m}$

h = is the altitude of the wind turbine in meters m

T_o = is the sea level standard temperature = 288.15 K

g = Earth surface gravitational acceleration = 9.80665 m/s^2.

R = Universal Gas Constant = 8.31447 $\frac{J}{mol\ K}$

M = Molar mass of dry air = 0.0289644 $\frac{kg}{mol}$

R_{da} = Dry air pressure = 287.05 $\frac{J}{kg\ K}$

ϕ – Relative humidity

R_v = Specific gas constant for water vapor = 461.495 $\frac{J}{kg\ K}$

A - Rotor swept Area of the wind turbine

C_p = Coefficient of performance

N_g = Generator Efficiency.
N_b = Gearbox transmission box Efficiency
$\left(\frac{t}{Z_r}\right)^{\alpha}$ = Rayleigh Wind distribution
U_r = Rayleigh Wind Mean
K_g = Exponential efficiency decay for the wind turbine generator.
K_b = Exponential efficiency decay for the wind turbine gearbox.

2.6 *Diesel Generator Model*

The model for the diesel generator utilized is the following:

$$S(t)_{DG_{ij}} = \left(\frac{F_{v_{ij}}}{F_{l_{ij}}}\right)\beta_{ij} * I * N_\beta e^{-K_\beta t}$$

Where:
F_v = Fuel volume in diesel generator i of size category j.
F_l = Minimum volume required for production in diesel generator i of size category j.
β_{ij} = is the Fuel Conversion Rate capacity for the diesel generator number i of size category j.
I = Coefficient of impurities in fuel.
N_β = Diesel generator efficiency.
K_β = Parameter of lifecycle exponential decay

Regarding the conversion rate capacity β, it is defined as the fuel utilization in liters per hour, divided by the current output of the generator in kW, e.g. a generator that consumes 10 L/hr of fuel at 20 kW output, would be 10/20=0.5 L/hr/kW.

2.7 *Electric Battery Model*

The electric battery reacts when there is need of more electricity (pull from available stored) or when there is excess electricity (push into the battery). Hence the expression is:

$$EB(t)_{ij} = \begin{Bmatrix} EB(t-1)_{ij} * D_{ij} + b_p(t) * C_{in_{ij}}, \forall b_p(t) > 0 \\ EB(t-1)_{ij} * D_{ij}, \forall b_p(t) = 0 \\ EB(t-1)_{ij} * D_{ij} - b_p(t) * C_{out_{ij}}, \forall b_p(t) < 0 \end{Bmatrix}$$

Where:
$EB(t)_{B_{ij}}$ = electricity in kWh stored in the current time step.
$EB(t-1)_{B_{ij}}$= electricity (kWh) stored in previous time step.
D_{ij} = depletion factor when the electricity remains stored.
$b_p(t)$ = is the partial electric balance at the current time step.
$C_{in_{ij}}$ = efficiency for pushing electricity into battery.
$C_{out_{ij}}$ = efficiency of pulling electricity from battery.

And the partial electric balance $b_p(t)$, it is defined as the production of electricity from the electric supply components mentioned before.

3. Methodology

The system is evaluated using a Monte-Carlo simulation as follows:

Step 1: Calculate the environmental factors for solar irradiation, temperature, and wind speed using statistical methods, and present such expected values according to the timestep selected for the simulation.

Step 2: Calculate individual contributions of electric production, for all components from *i*=1 to *n,* and for all sizes *j*=1 to *m*. This calculation must be done for all components of all types.

Step 3: Summation of all electricity production contributions into a single value.

Step 4: Decision making: if the electricity produced is more than needed, push excess into battery. If electricity produced is less than needed, pull the remaining from the battery.

Step 5: Repeat until 1 out of 2 conditions is satisfied:

- the electric balance is negative, or,
- all time steps are completed

Step 6: Cost Evaluation: find by implementing the costs functions described in equations 1 to 11.

Step 7: Unfeasibility penalty: if there is any blackout, apply a cost penalty.

3.1 Optimization with Genetic Algorithm

The first stochastic optimization method utilized to find a configuration for the microgrid is the genetic algorithm, with the following properties.

- Population size = 100
- Convergence = 50 iterations without improvement
- Elite = top 10%
- Mutation = 5%
- Reproduction Method = Roulette

The Chromosome is encoded as follows:

$Chromosome = G_1, G_2, G_3, G_4, G_5$

Where:

G_1 = Number of Solar Panels, integer values from 0 to 1000

G_2 = Number of Wind Turbines, int. values from 0 to 1000

G_3 = Number of Diesel Generators, int. values from 0 to 1000

G_4 = Number of Converters, int. values from 0 to 1000

G_5 = Number of Batteries, int. values from 0 to 1000

The genetic algorithm was implemented as follows:

Step 1 - Initialization: Create a random population of N=100 chromosomes, each gene is a random value within the defined limits mentioned above.

Step 2 – Evaluation with Monte-Carlo Simulation: Each of the chromosomes undergoes the Monte-Carlo simulation, to find the total cost.

Step 3 – Ranking the solutions: The population is ranked from best to worst according to the Total Cost.

Step 4 – Elite identification: The best chromosomes are identified, and automatically survive until next generation.

Step 5 – Check for convergence & End if needed: If the alpha individual is the same as the previous generation, increase a counter. If this counter exceeds the threshold of convergence, stop.

Step 6 – Reproduction by roulette: The top individuals receive a higher portion of probability to be selected for reproduction and the lower ranking individuals receive a smaller probability of being selected. Then a random number is generated to select 2 chromosomes that go to reproduction, and they generate 2 new offspring by combining their gene values. This process is repeated until the offspring generated is equal to the size of the population minus the elite portion.

Step 7 – Mutation: Individuals from the offspring are randomly selected to undergo the process of mutation: a random gene will change to a random value.

Step 8 – Repeat: We start the new iteration from step 2.

The genetic algorithm has been widely used as an approximation method of optimal solutions in complex systems including the Renewable Energy Integration, such as the works of M.S. Ismail, et al in 2014 where they describe a similar utilization, by M. J. Mayer et al in 2020, where they extended for multi objective optimization, and several others found in the literature.

3.2 Firework algorithm

The firework algorithm approximates the optimal by an iterative approach, in which the combinations are represented by a sequence of values called sparks.

The firework algorithm has been used successfully in previous projects pertaining to microgrids, such as the work of Jadoun et al in 2018 in which they use it to manage various dynamic loads on a microgrid by taking advantage of the method's high adaptability, or the work by Want et al in 2017 in where they optimize the microgrid merely by firework algorithm, among others. The parameters of the firework algorithm employed are the following:

- Population size = 100
- Explosion Amplitude = each firework produces 3 new individuals in the neighborhood.
- Explosion Interval = Each generation.
- Spark range = Ranked box percentage of total range for each gene.
- Convergence = 50 iterations without improvement.

The firework algorithm is encoded as follows: $Firework = Spk_1, Spk_2, Spk_3, Spk_4, Spk_5$

Where:

Spk_1 = Number of Solar Panels, int. values from 0 to 1000.

Spk_2 = Number of Wind Turbines, int. values from 0 to 1000

Spk_3 = Number of Diesel Generators, int. from 0 to 1000

Spk_4 = Number of Converters, int. values from 0 to 10,000

The firework algorithm is implemented as follows:

Step 1 - Initialization: Create a random population of N=100 fireworks, with each spark showing a random value within the defined limits mentioned above.

Step 2 – Evaluation with Monte-Carlo Simulation: Each of the fireworks undergoes the Monte-Carlo simulation, to find the total cost.

Step 3 – Ranking the solutions: The population is ranked from best to worst according to minimum cost.

Step 4 – Check for convergence & End if needed: Check if the alpha individual is the same as the previous generation, and decide to continue or to stop in a similar fashion as step 5 from the genetic algorithm.

Step 5 – Trimming Population: Trimming the population to include only the top N-individuals such that population size remains consistent within the iterations. This step is necessary since each firework will create child fireworks, thus increasing the size of the population temporarily, as the previous iteration's fireworks do not cease to exist from the population unless they are ranked-out of the top N-individuals.

Step 5 – Distribute box ranges: The ranks are given a sequential box range, in order from 1% to 100%, where the top individuals receive a **lower** spark range and the lowest large box range of 100%. In our example we have population size =100 meaning each firework obtains a 1% increase in their box range, from 1% at the top to 100% at the bottom.

Step 6 – Explosions: Each firework will produce in our case 3 new fireworks by creating random spark values according to the corresponding box range, meaning the new spark values will be: **current_spark_value ± spark range %.** This will create new fireworks that are close to the original values, for high performing individuals, and increasingly different from the original for low ranking individuals, thus allowing a balance of exploitation vs exploration.

Step 7 – Repeat: We start the new iteration from step 2.

3.3 Analogies and similarities between the Firework Algorithm and Genetic Algorithm

In the fireworks algorithm, each chromosome is called firework, and it works by implementing variances in each spark, which can be considered the analogous to the genes of the genetic algorithm.

Additionally, we do not have a need for elite in the firework algorithm, since all the solutions keep existing until the next iteration is evaluated, and fade out only when better solutions are found. Moreover, the explosions from the firework algorithm are analogous to the reproduction and mutation steps from the genetic algorithm, since these steps allows new combinations to enter into the population.

4. Case Study

Certain building in Kuwait has the following data:

Table 1: Daily means per month

Month	Electric Demand: Daily Mean (kW)	Solar Irradiation: Daily Mean (kWh/m2/day)	Temperature: Daily Mean (°C)	Wind Speed: Daily Mean (m/s)
Jan	195.8	3.40	14.15	5.56
Feb	198.3	4.37	15.29	5.83
Mar	205.6	5.20	18.89	5.66
Apr	205.4	5.92	24.18	5.36
May	204.6	6.88	30.14	5.66
Jun	198.9	7.96	34.09	7.63
Jul	202.3	7.59	35.95	7.36
Aug	196.3	7.26	36.01	6.43
Sep	198.4	6.52	33.15	5.73
Oct	202.6	5.07	28.58	5.02
Nov	204.2	3.60	21.98	5.47
Dec	200.5	3.07	16.44	5.63

The daily random variability from time step to step is 5%. The solar irradiation, temperature and windspeed values are downloaded from the NASA Prediction of Worldwide Energy Resource (POWER) database. The annual inflation rate is set to 7% during the next 25 years. The price of diesel is 0.374 $/L. The components considered are the following:

Batteries of 6V, 6.94 kWh, (model: Vision CP12240D) with capital and replacement costs of $1500 dollars. 80% round-trip efficiency, 40% minimum state of charge, and 12 years lifetime.

AC-Diesel Generators of 15kW with Capital Cost of $6,690 and zero salvage value. Fuel conversion rate of 0.08 L/h/kW, lifetime of 2 years with 30% minimum load ratio.

Solar panel-cells of 10 kW rated capacity, producing in DC, with Capital Cost of $30,000 zero salvage value, $300 annual costs, 20 years lifetime and 80% derating factor.

Generic Wind Turbines of 3 kW rated capacity, producing in DC, with a Capital Costs of $14,797 lifetime of 15 years, and 25 m hub-height. No salvage value.

Converters of 1000kW capacity with Capital Cost of $300, no salvage value, lifetime of 15 years. Efficiency 90% for inverter and 85% for the rectifier.

5. Results

5.1 *Genetic Algorithm Results*

The Genetic Algorithm mentioned above was implemented in Matlab and yielded the following results according to the Monte-Carlo simulation:

The alpha chromosome was convergent to: [133, 55, 0, 870, 3] found after 112 generations. This result can be interpreted as follows:

- Number of Solar Panels: 133 for a total rated output capacity of 1330 kW.
- Number of Wind Turbines: 55 for a rated capacity of 165 kW

- Number of Diesel Generators: 0
- Number of Electric Batteries: 870 for an overall rated capacity of 6037.8kW.
- Number of Converters: 3 to have an overall rated capacity of 3000 kW.

Yielding a total cost of:

- Total Cost = 7'432,368 USD

  The computer utilized was an HP with the following specifications:
- Processor: Intel(R) Core(TM) i3-3240 CPU @ 3.40GHz 3.40 GHz
- RAM: 6.00 GB (5.89 GB usable)
- Operating System: Windows 10 Pro, with 64-bit operating system, x64-based processor

The Matlab version utilized was:

- MATLAB R2013b

For an estimated processing time of: 18.83 seconds.

The convergence was found after aggressive improvements were made in the objective function during the first 20 generations, after which the method was slower to find improvements, and finally converging after 112 generations as shown in fig. 6 below.

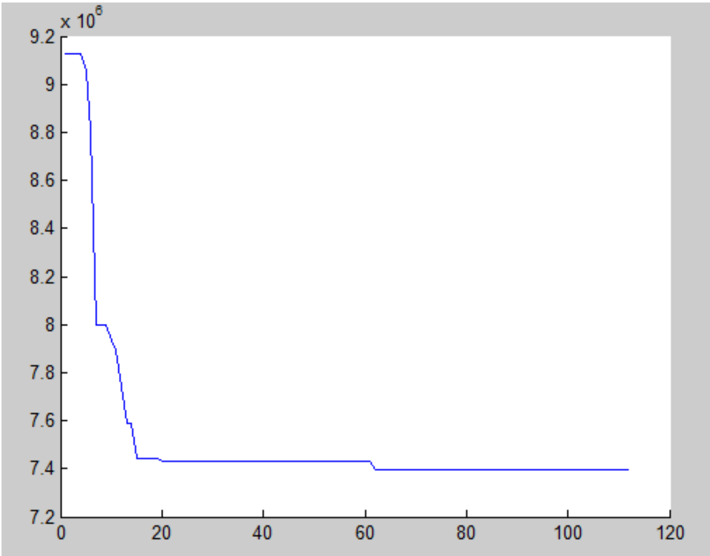

Figure 6: Total Cost vs Generation Number produced by Genetic Algorithm.

5.2 *Firework Algorithm Results*

The Fireworks Algorithm mentioned above was implemented in Matlab and yielded the following results according to the Monte-Carlo simulation:

The alpha firework was convergent to: [122, 51, 0, 873, 3] found after 145 generations. This result can be interpreted as follows:

- Number of Solar Panels: 122 for a total rated capacity of 1220 kW.
- Number of Wind Turbines: 51 for a rated capacity of 153 kW.
- Number of Diesel Generators: 0
- Number of Electric Batteries: 873 electric batteries for an overall rated capacity of 6058.6kW.
- Number of Converters: 3 to have an overall rated capacity of 3000 kW.

Total Cost = 7'129,511 USD

The computer utilized was the same as for the genetic algorithm shown above.

The Matlab version utilized was the same as shown above (MATLAB R2013b).

For an estimated processing time of: 56.99 seconds.

The convergence is found after high improvements in the objective function during the first 10 iterations, after which the method was slower to find improvements from iteration 11 to 75, and finally converging after 145 generations as shown in fig. 7 below.

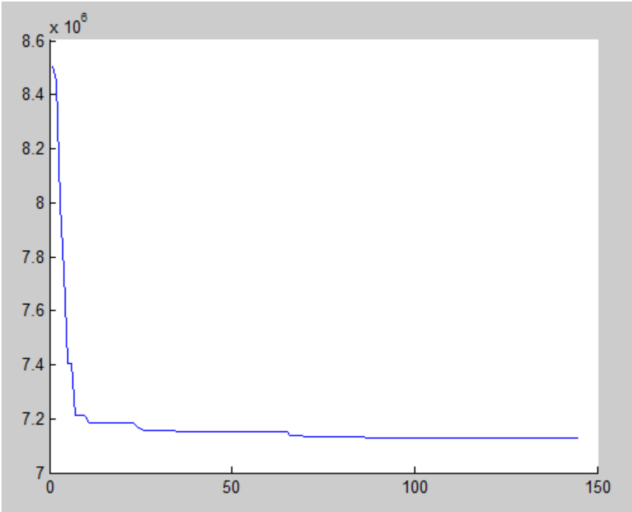

Figure 7: Total Cost vs Iteration Number produced by Firework Algorithm

5.3 *Differences in results*

It was noted that given the nature of the Monte-Carlo simulation, as well as the stochastic approach of the optimization algorithms, each time a solution was found, the algorithms yielded slightly different results, and as such, a comparison of 10 results is made in order to have a better understanding of the differences and similarities between the 2 methods:

Table 2: Genetic vs Firework Algorithm Results for 10 trials

Trial	Genetic Algorithm Total Cost	#Iterations for Convergence	Running Time (seconds)	Fireworks Algorithm Total Cost	#Iterations for Convergence	Running Time (seconds)
1	$ 7,432,368	112	18.83	$ 7,129,511	112	56.99
2	$ 7,103,763	122	20.26	$ 7,153,455	144	53.21
3	$ 7,261,996	247	39.94	$ 7,075,527	136	50.00
4	$ 7,279,631	142	22.66	$ 7,118,224	129	47.55
5	$ 7,332,898	82	14.41	$ 7,071,309	216	80.83
6	$ 7,134,485	110	19.38	$ 7,113,291	70	26.55
7	$ 7,173,246	130	20.24	$ 7,099,791	149	54.77
8	$ 7,073,233	90	14.41	$ 7,091,224	117	43.92
9	$ 7,148,373	109	17.05	$ 7,063,342	218	81.54
10	$ 7,525,647	66	10.64	$ 7,065,821	140	51.68

From the above table, we compare the 2 algorithms by taking the average, maximum value and minimum values achieved for each of the categories shown above, yielding the following shown in table 3.

Table 3: Genetic vs Firework Results comparison

	Genetic Algorithm Total Cost	#Iterations for Convergence	Running Time (seconds)	Fireworks Algorithm Total Cost	#Iterations for Convergence	Running Time (seconds)
Average	$ 7,246,564	121	20	$ 7,098,150	143	55
Max	$ 7,525,647	247	40	$ 7,153,455	218	82
Min	$ 7,073,233	66	11	$ 7,063,342	70	27

And these values can be considered a representative summary of 10 trials of the Genetic Algorithm reaching a solution, as well as 10 trials of the Firework reaching a solution to the same problem of renewable energy integration problem with high inflation scenario presented above.

6. Discussion

We can see from table 3 shown above that the average total cost obtained by the Firework Algorithm appears to be lower than the average total cost obtained by the Genetic Algorithm by as much as $148,415 USD. This leads us to believe that the Firework Algorithm is performing better than the Genetic Algorithm when finding solutions to this problem.

Additionally, the maximum value obtained for total cost from the Genetic Algorithm appears to be larger than the Firework Algorithm, by $372,192 USD. This also leads us to believe that Firework Algorithm is outperforming the Genetic Algorithm when solving this problem.

Moreover, the minimum value for total cost achieved by the Firework Algorithm is smaller than the minimum achieved by the Genetic Algorithm by a small amount ($ 9,891 USD), which is also in concordance with our previous findings regarding the Firework Algorithm outperforming the Genetic Algorithm.

We can see also that regarding the average running time to reach a solution is of 20 seconds for the Genetic Algorithm and 55 seconds for the Firework algorithm, which leads us to believe that the Genetic Algorithm is faster in reaching a solution.

A comparison between the maximum amount of time to reach a solution is 40 seconds for the GA and 82 seconds for the FA, which also leads us to believe that the GA is faster than the FA to converge to a solution. The same is found when comparing the minimum values for processing times: 11 seconds for GA and 27 seconds for the FA, which adds to the conclusion that Genetic Algorithm is faster than the Fireworks Algorithm to find a convergence.

Regarding the number of iterations needed, the Genetic Algorithm required in average 121 iterations for convergence while the Firework Algorithm required 143, which may be leading to conclude that the Genetic Algorithm requires less computational work than the Firework Algorithm, however more formal analysis on this matter is needed at this point, to analyze the number of operations performed inside each of the iterations for each of the algorithms. Moreover, comparing the maximum number of iterations needed: 247 for the GA and 218 for the FA, apparently the Firework Algorithm can sometimes require more iterations than the Genetic Algorithm, and the minimum number of iterations to reach convergence was 66 for the GA and 70 for the FA.

From this work we can highlight the following 2 findings:

Finding 1: Genetic algorithm took less iterations to converge to a solution than the firework algorithm, which opens the question regarding the amplitude of explosion parameter of the firework algorithm: Our group hypothesis is that greater explosion amplitude may render smaller number of generations in the firework algorithm to converge.

Finding 2: It was noted that each iteration of the firework algorithm was slower to solve than the genetic algorithm, possibly due to the fact that the population increases temporarily after the firework explosion step and before the trimming step in the firework method.

As a conclusion, both methods appear to work well in combination with the Monte-Carlo simulation, even after the introduction of high inflation economical scenarios. As such, we conclude that that both methods can be safely used to optimize the design of hybrid micro-grids in the future when economical scenarios become more uncertain.

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