Developing a Framework for Determining Optimum Dispatch of Energy to a Building from Conventional and Renewable Sources

Sultan Ahmad
Purdue University, ahmad56@purdue.edu

William Travis Horton

Developing a Framework for Determining Optimum Dispatch of Energy to a Building from Conventional and Renewable Sources

Sultan AHMAD[1]*, W. Travis HORTON[2]

[1]Purdue University, Lyles School of Civil Engineering,
West Lafayette, IN, USA
+1 (765) 237-7802, sultan.ahmadsid@gmail.com

[2]Purdue University, Lyles School of Civil Engineering,
West Lafayette, IN, USA
+1 (765) 494-6098, wthorton@purdue.edu

* Corresponding Author

ABSTRACT

In an optimally designed grid-connected system with distributed energy resources where the grid plays the role of an energy buffer, it is interesting to analyze the economic feasibility to employ energy storage systems. A grid-connected system synchronizes with the power fluctuations, lowering the costs of energy compared to the cost of using conventional energy storage systems. An adaptive code is developed using computer programming that is used for lifetime simulation of the energy dispatch system with a specified time step and for optimization algorithm with comprehensive reliability/cost assessment. The results can be extended to a long period considering various economic factors. The programming code can be integrated with any system model, which can be flexibly implemented to any number of applications. In the present work, a strategic framework is developed for determining the optimal energy technology allocation to a typically selected commercial building located in the United States. The optimum design and management strategy of grid connected renewable generating systems composed of energy conversion units is considered. The provision of a hybrid system of energy storage is investigated. A genetic algorithm optimization-based approach is adopted for carrying out the optimization. The optimization of the set problem consisted of the minimization of the total lifecycle costs considered as the objective function, whereas the fulfillment of the users demand for energy was considered as the key constraint. The most suitable systems with an operation on hourly basis and the best strategy for the storage of energy were considered to generate the optimization results providing the optimal size and total cost of the system components. Furthermore, the possibility of using alternative energy dispatch systems was explored that might reduce the total lifetime costs below the cost of a benchmark case in which the entire demand for electricity is fulfilled from the grid. Four scenarios were analyzed to measure the impact of planning and operating the distributed energy resources: typical, off grid, on grid, feed-in-tariffs.

1. INTRODUCTION

In the recent times, increased energy demands have led to a dramatic rise in the consumption of fossil fuels and this in turn has led to highly raised energy prices and environmental pollution issues. Considering the effect of using fossil fuels on the environment, the necessity for using renewable energy (RE) to meet the increasing energy demand has been developed. The main challenges of using renewable energy include the associated high costs and the unpredictability of the renewable energy technologies. In this context, a promising scenario would be to overcome the challenges associated with renewable energy by integrating the renewable energy sources in order to meet the demand of energy in each area (Sharafi & ELMekkawy, 2014).

With the help of a widespread literature search, some implications are drawn regarding the Distributed Energy Resources [DER] systems and about its modeling research. It becomes evident that almost all DER systems and their modeling research originates from Asian and European regions, not dealing explicitly with the US regions energy policy. There has been no research which investigates a large range of energy technologies considering simultaneously- renewable (e.g. wind, solar), modern (e.g. geothermal pumps, different type of fuel cells), conventional (e.g. boilers, engines) and storage (e.g. pumped storage, batteries). Very few researches study technical, economic and environmental aspects all clubbed together (Mallikarjun & Lewis, 2014).

The design optimization of a DER system is considered critical, particularly when the net present cost of a DER system is high and therefore, the adaptation of a substandard optimal design would have a negative impact on the economics of the DER system significantly over a long run. In addition, the Kyoto protocol, implemented in the year 1997, obligates that the countries, which were industrialized should reduce their greenhouse gas emissions. Therefore, there is a need for research that would help in minimizing the lifetime costs as well as emissions from fossil fuel (Sharafi & ELMekkawy, 2014).

In the present study, an attempt is made to develop a multi-objective strategic framework for a typically selected commercial building with a main objective to determine the optimal size of energy components allocated for the DER system. The proposed framework considers economic, technical, and environmental concerns simultaneously. The minimization of the total annual energy costs and CO_2 emissions is considered as the problem's optimization target, while the main constraint is the fulfillment of the users' requirement for the electricity. An optimization tool is developed simulating an optimization algorithm. The heating, cooling, and electricity load profile on hourly basis are defined for the building in a reference year. The input data to run the model include hourly weather data of the year and the actual cost of the technologies. The objective functions are optimized by using the input data into the energy balance equations and relevant constraints. To achieve this goal, the research is extended to the following four sub-objectives:

1. Carry out review of the relevant literature on studies pertaining to existing modelling and simulation of various DER systems and applications of different techniques for optimization of the DER systems.
2. Formulate models to calculate the annual load requirements and CO_2 emissions by the DER system.
3. Implement optimization techniques in order to ensure that the desired energy efficiency is achieved without exceeding the level of CO_2 emissions beyond maximum permissible limits.
4. Conduct case studies on the optimization of the selected DER systems.

Different groups, who can be benefitted from the framework proposed through the present research, are listed below:

1. Occupants: People would be aware of the energy systems that might match with their requirements in a better way.
2. Policymakers: They will be able to assess the effect of subsidy schemes, such as steering taxes, net-metering or feed-in-tariffs, and carbon tax.
3. Companies: Information on sizing the system such that it is appealing to the users.
4. Researchers: People would be able to study novel technologies, which can be integrated with the DER.

2. RESEARCH METHODOLOGY

2.1 Problem Description

The trigeneration system is composed of four sources of energy, four transformation components, two storage components, and six end-uses. The four energy sources are solar, wind, electricity grid and natural gas grid. Energy conversion unit is composed of a photovoltaic (PV) panel, a wind turbine, an electrolyzer and a cogeneration fuel cell. The two types of storages are batteries and hydrogen tank. The energy flux of the proposed system framework is presented with a schematic diagram in Figure 1. Surplus energy is stored in respective storage components when the production of energy is more than the required load. Batteries are used to store the excess energy, which is produced for electricity. A part of excess energy, generated for electricity demand, is stored into batteries and the remaining part of the energy is put into the electrolyzer to convert into hydrogen. Electrolyzer produced hydrogen is transported and stored in the hydrogen tank (H_2-tank). Based on the H_2 tank capacity and the state of charge present in batteries, the fuel cell and batteries can provide the intended power to meet the load requirements when the energy produced by the electricity type does not meet the load. Electricity from the grid can be used as a source of an emergency power supply when the fuel cell and batteries are not able to satisfy the energy deficit.

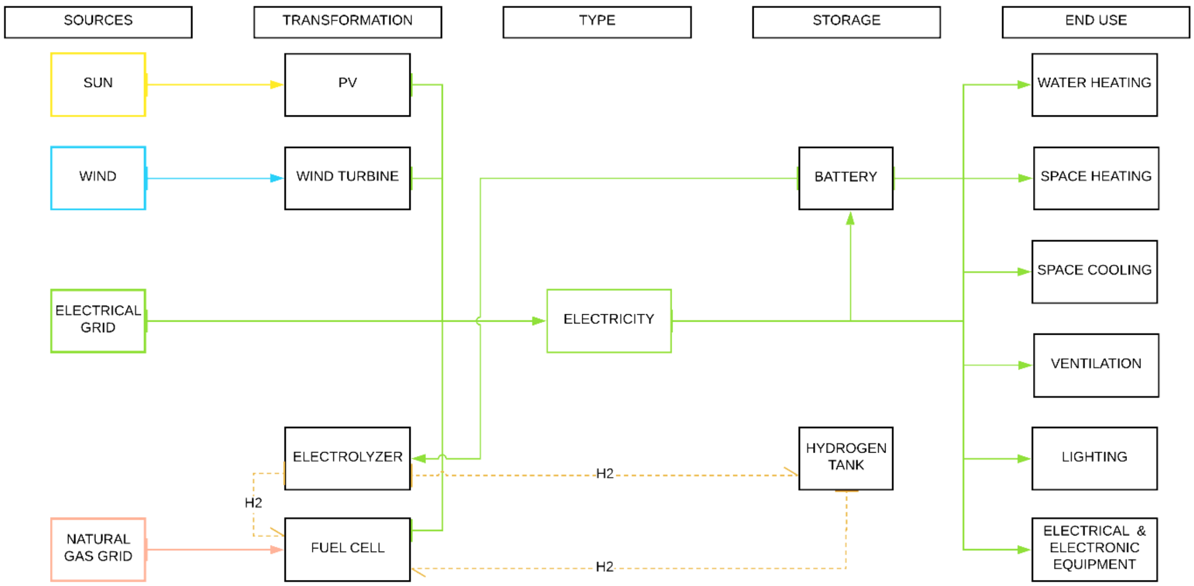


Figure 1: Energy flux of the proposed system framework

2.1.1 End Use: The reference building is a medium office building located in Albuquerque, New Mexico, United States. The building has a total rooftop area of 4982 m^2. Main constraint is the fulfillment of the occupant's load demand that includes electricity, space heating, space cooling and hot water. Electricity grid, PV panels, wind turbines, and electrolyzer produce electricity to meet the energy requirement of the users. Figure 2 shows the average monthly energy use of the building per type of electric load. The total energy load of the building is 4.25E+05 kWh.

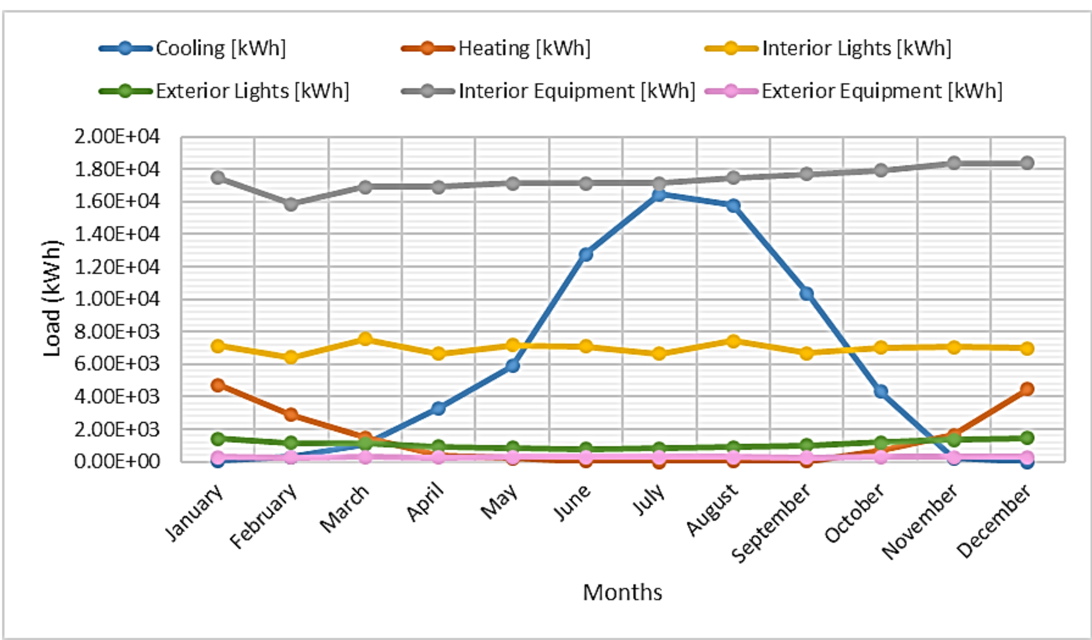


Figure 2: Monthly energy consumption by the building for different electric load type

The energy load requirement of the building is fulfilled by electricity. Energy load, E_{Load} can be classified as a combination of the Heating Load (L_H), Cooling Load (L_C), Electricity Load (L_{EL}), Hot Water Load (L_{HW}). All energy loads are provided in kWh, as shown in Figure 2. Based on the energy usage, electricity seems to be the primary source of heating.

3. MATHEMATICAL MODELS

The mathematical models, utilized in the simulation of conversion and storage components, are summarized below.

3.1 PV Panel

Photovoltaic cells or solar panels are devices that transform solar energy into electricity. Solar irradiation, wind velocity and air temperature data are used in the model in order to estimate the performance of the PV system. This data is obtained either from real-time measures or from online database and are location specific. The amount of energy supplied for each hour by the solar panel is measured using this data. A fixed tilt angle of 55° is used for the selected building location. The energy produced by PV panels can be calculated using Equation (1) (Ekren & Ekren, 2010).

$$E_{PV}(t) = (\eta_{PV} A_{PV}) I_T(t) \tag{1}$$

where, η_{pv} is the module efficiency of PVs, A_{PV} is the solar panel area (m^2), and I_T (t) is total solar radiation (hourly) received by the tilted surface. A constant η_{pv} equal to 15% is assumed in this study. The module efficiency value accounts for loss of power in solar panels due to losses in inverter, shade, temperature change, dirt, etc. The main constraint governing the conversion of solar energy into electricity is the direct dependence on the incoming radiation. The device may generate more power than its nominal output if the radiation is higher than that at the normal rating conditions (1000 Wm^{-2}). The rated panel power output is 6.2 kW.

3.2 Wind Turbine

In wind turbines, conversion of wind kinetic energy into electrical energy results in generation of wind power. The energy generated from a wind turbine can be calculated using Equation (2) (Ekren & Ekren, 2010).

$$E_{WT}(t) = \begin{cases} 0, & v < V_c \\ \frac{1}{2} C_p \rho A_{WT} v^3(t) \Delta t, & V_c < v < V_r \\ 0, & v > V_o \\ P_{WG,r}, & V_c < v < V_r \end{cases} \tag{2}$$

V(t) is an input variable and is defined as the hourly wind speed. C_p is the coefficient of performance, which is calculated as the ratio of the power output to maximum power and is obtained from the manufacturer's handbook. A_{WT} denotes to rotor swept area and ρ refers to the air density. V_c and V_r are the cut-in and rated wind velocity, respectively. V_c is taken as 4 m/s while V_r is taken as 14 m/s. V_o is the cut-off wind speed and is fixed at 20 m/s. $P_{WG,r}$ refers to the rated power of wind turbine which is 6.5 kw (Dufo-López & Bernal-Agustín, 2008).

3.3 Battery

In the battery-based renewable energy system, the battery size continuously changes due to the intermittent supply of electricity from solar panels and wind turbines. The state of charge (SOC) of the battery at any time period is determined using Equation (3):

$$SOC(t) = SOC(t-1) \pm \frac{E_{bat}(t)}{P_{bat}} \cdot 100 \tag{3}$$

where, SOC (t) and SOC (t-1) are the state of charge of battery in time interval t and t-1, respectively. $E_{bat}(t)$ is energy charged or discharged by the battery during hour t. P_{bat} is 10 kW which is the nominal capacity of battery. The sign is positive while charging and negative when it is discharging. Until it exceeds the lower limit of SOC_{min}, which is 30%, the battery will provide electricity to the system. In addition, the battery can be charged until 100% of SOC_{max} is achieved. (Abedi et al., 2012). The battery is in a charging state when the combined output of PV panels and wind turbines is greater than the load requirement. The battery is in discharge status when the combined output of PV panels and wind turbines is smaller than the demand for load. The charge quantity of the battery at time t can be obtained by Equation (4).

$$E_{bat}(t) = E_{bat}(t-1) \times (1-\sigma) \pm \left[E_{PV}(t) + E_{WT}(t) - \frac{E_{Load}(t)}{\eta_{inv}} \right] \times \eta_{bat} \tag{4}$$

where E_{bat} (t) and E_{bat} (t-1) are the battery charge at time t and t-1, σ = 5%, η_{inv} = 90 % represents the inverter efficiency, E_{load} refers to the load requirement, and η_{bat} = 80% is the battery efficiency in charging state. For this study, the discharge efficiency of battery is taken as η_{bat} = 100%.

3.4 Electrolyzer

Oxygen and hydrogen are extracted from water through electrical energy with the use of an electrolyzer. $Elec_{EL}$ is the electrical consumption capacity of the electrolyzer and is modeled as a function of nominal hydrogen mass flow rate (Q_{n-H_2}) (kg/h), and actual hydrogen mass flow rate (Q_{H_2}= 0.9 Q_{n-H_2}) (kg/h), as given in Equation (5). In this study, heating value, HHV_{H2} is considered as 38.7 kwh/kg, β_E = 40 kwh/kg and α_E = 20 kwh/kg, (Dufo-López & Bernal-Agustín, 2008)..

$$Elec_{EL} = \alpha_E Q_{n-H_2} + \beta_E Q_{H_2} \tag{5}$$

where, α_E, β_E are defined as the coefficients of electricity utilization curve. The efficiency of the electrolyzer is expressed as the produced HHV_{H2} divided by the consumption of electricity, as shown in Equation (6) (Dufo-López & Bernal-Agustín, 2008).

$$\eta_{EL} = \frac{Q_{H_2} \times HHV_{H_2}}{Elec_{EL}} \tag{6}$$

3.5 Fuel Cell

Fuel cells (FC) are selected as backup generator as they convert hydrogen and oxidants chemical energy into electrical energy. The total power output for a FC is defined through a function ($H_{2,cons-FC}$) (kg/h) which is the hydrogen consumption of the fuel cell and it is shown in Equation (7) (Dufo-López & Bernal-Agustín, 2008).

$$H_{2_{cons-FC}} = (\alpha_{FC} \times P_{n-FC}) + (\beta_{FC} \times P_{a-FC}) \tag{7}$$

where α_{FC}, β_{FC} are defined as the coefficients of hydrogen consumption curve and is an input of the model. Also, α_{FC} = 0.005 kg/kwh, β_{FC} = 0.06 kg/kwh. P_{n-FC} (kW) is defined as the nominal output power while P_{a-FC} (kW) is defined as the actual power of fuel cell. The manufacturers' manual recommends the maximum output power to be 90% of the nominal power. The energy efficiency is η_{FC} and it is calculated using Equation (8), where, LHV_{H2} = 33.3 kWh/kg.

$$\eta_{FC} = \frac{P_{a-FC}}{H_{2_{cons-FC}} \times LHV_{H_2}} \tag{8}$$

The energy produced by fuel cell during hour (t) is obtained by Equation (9):

$$E_{FC}(t) = H_{2_{cons-FC}}(t) \times LHV_{H_2} \tag{9}$$

3.6 Hydrogen Tank

To estimate the efficiency of the hydrogen tank, the charging efficiency of the electrolyzer and the discharge efficiency of the FC is taken into consideration. The electrolyzer would be used to fill the hydrogen tanks if the power produced from the PV/wind system is greater than the load requirement at time step t. Hydrogen level of the hydrogen tank at time t ($H_{2,level}$ (t)) is based upon hydrogen level at time t-1 (H_{2level}(t-1)), hydrogen consumption by fuel cells at time t,($H_{2,cons-FC}$ (t)), and hydrogen production by the electrolyzer at time t (Q_{H2}), Equation (10).

$$H_{2_{level}}(t) = H_{2_{level}}(t-1) + Q_{H_2}(t) - \frac{H_{2_{cons-FC}}(t)}{\eta_{H_{2-tank}}} \tag{10}$$

where, $\eta_{H2-tank}$ is defined as the efficiency of the hydrogen tank storage which specifies losses associated with pumping and leakage. $\eta_{H2-tank}$ is assumed 95% for this study. Additionally, the hydrogen level is demarcated with upper limit defined as the tank's nominal power while the lower limit is set as 5% of rated capacity (Kashefi et al, 2009). The capacity of hydrogen tank at time step t is obtained by Equation (11):

$$P_{H_{2_{tank}}}(t) = H_{2_{level}}(t) \times HHV_{H_2} \tag{11}$$

4. OPTIMIZATION MODELLING

A novel approach is presented for optimizing the size of the DER system. The genetic algorithm (GA) is utilized to minimize the objectives. GA is a method based on a natural selection process that mimics biological evolution to solve both constrained and unconstrained optimization problems. The algorithm modifies a population of individual solutions repeatedly. The GA randomly selects individuals from the current population at each stage and uses them as parents to create the children for the next generation. The population "evolves" toward an optimum solution over successive generations. An adaptive code is developed using multi-paradigm programming language that is used for the optimization algorithm.

4.1 Objective Functions

The objective functions to be minimized are:

- The total cost over the lifetime: Cost ($)
- The CO_2 emissions: CO_2 (kg/year)

The complete lifetime of a system is considered to be 25 years, similar to the life of solar panels, as they are considered to be the components having a better lifetime (Dufo-López & Bernal-Agustín, 2008).

4.1.1 System Installation Costs: The system installation cost consists fuel cost, investment cost, replacement cost, operation and maintenance cost, spread over the project lifetime Equation (12).

$$Installation\ Cost = \sum_{j} \left(\left[C_{I,x} + C_{O\&M,x} \times \frac{1}{CRF(i,T)} + C_{rep,x} \times K_x \right] \times P_x \right) + C_{fuel} \times fuel_{cons,yr} \times \frac{1}{CRF(i,T)} \quad (12)$$

where, x is system type, C_{Ix} is the capital cost per unit ($/unit), $C_{rep,x}$ is the replacement cost per unit ($/unit), $C_{O\&M,j}$ is the operation and maintenance cost per unit ($/unit), P_x is the size of each system. C_{fuel} is the fuel cost per unit ($/lit) and $fuel_{cons,yr}$ is the consumption of fuel per year (lit/year). K_x is net present cost and CRF is the capital recovery factor, and are represented by Equation (13, 14, 15) (Abedi et al., 2012; Dufo-López & Bernal-Agustín, 2008; Kashefi et al., 2009).

$$K_j = \sum_{n=1}^{R} \frac{1}{(1+i)^{L\times n}},\ \begin{cases} R = \left[\frac{T}{L}\right] - 1 & T\%L = 0 \\ R = \left[\frac{T}{L}\right] & T\%L \neq 0 \end{cases},\ CRF = \frac{i(1+i)^T}{i(1+i)^T - 1} \quad (13, 14, 15)$$

where, the interest rate is i, L and R are defined as lifetime and number of component replacements, respectively. T is the lifetime of the project that is assumed to be 25 years in this analysis.

4.1.2 Net Present Value of System Savings: NPV is presented in dollars which is estimated using sum of the total future cash flows over the investment lifetime. It is a common metric where the present value of future cash flows is calculated using the discount rate. For DER, the resulting energy savings are termed as future cash flows (House, 2017). NPV of each system (S_j) is calculated using the Equation (16):

$$NPV(S_j) = \sum_{j} \sum_{n=0}^{T} \frac{Cash\ Flow_n}{(1+d)^n} \quad (16)$$

Where, T is the lifetime of the project, n is a year within the lifetime, cash flow is the system cost for years n = 0 through N and d is the discount rate. Table 1 provides the data required for the calculation of the system used:

Table 1: Input Data for Net Present Value

Parameter	System	Parameter	System
Electricity Cost per kWh	14%	Fuel Inflation Rate	2%
Discount Rate	6%	Annual Degradation	0.6%

4.1.3 CO_2 Emission Cost: In this research, an overall environmental profile of different energy generation technologies has been analyzed via the concept of carbon footprint. The purpose of such analysis is to evaluate the complete life cycle of the energy producing technology, ranging from resource and fuel mining through construction to operation and waste management (Edenhofer et al., 2011). The cumulative ton of CO_2 released by the system over a period of 1 year is considered to be the right estimate of pollutant emissions. A CO_2 cost is an economic metric that lets consumers determine whether to stop, reduce or continue polluting and pay for it. In this way, the overall environmental goal is accomplished in the most adaptable and least expensive way to society and, therefore, it can be used as the objective to be minimized. CO_2 cost is calculated by using Equation **(**17).

$$CO_2\ emission\ cost = \sum_{t=1}^{8760} P_j(t) \times \Delta t \times EF \times CO_{2_{\text{price}}} \quad (17)$$

where P_j is the capacity of the technologies. $CO_{2,price}$ is $ 0.055 per kg of CO_2 produced per unit of electrical energy generated (Brooks, n.d.). EF is known as the emission factor and it depends on the type of fuel or technology used. The emission factor for different renewable energy technologies is summarized in Table 2 (Milousi et al., 2019).

Table 2: Life cycle CO_2 emission factors of the analyzed DER systems

Type	Emission Factor (g CO_2/kWh)	Type	Emission Factor (g CO_2/kWh)
PV	26-60	**Hydrogen tank**	10-24
Wind Turbine	9-35	**Electrolyzer**	26
Battery	35	**Fuel Cell**	26

4.1.4 Total System Costs: The total system cost is estimated by adding CO_2 cost to the difference between the cost of system installation and cumulative future cash flows over the lifetime. It is presented using Equation (18):

$$Total\ Cost = [\text{Installation Cost} - \text{NPV}(S_j) + CO_2\ emission\ cost] \tag{18}$$

4.2 Decision Variables

Decision variables are number of components in each technology and capacities of the technology. The following vector summarizes the capacities of the systems: $P = \{P_{PV}, P_{WT}, P_{Bat}, P_{Tank}, P_{El}, P_{FC}\}$, where, P_{PV} is defined as the capacity of PV panels (kW), P_{WT} refers to the capacity of the wind turbine (kW), P_{Bat} is the capacity of battery banks (kWh), P_{Tank} links to the capacity of $H_{2\text{-tank}}$ (kWh), P_{EL} refers to the capacity of electrolyzer (kW), P_{FC} is known as the capacity of fuel cell (kW).

4.3 Constraints

Operation constraints are applied on the component's energy and storage levels. The energy flux in each time step ($E_j(t)$) must be less than the component capacity as shown in Equation (19).

$$E_j(t) \leq P_j(t) \times \Delta t \tag{19}$$

where, Δt is defined as time interval of 1 h. There is a constraint on the area usable for the installation of solar panels on the building roof, as shown in Equation (20).

$$A_{PV} \leq A_{max} \tag{20}$$

where, A_{PV} is the area for installing PV panels. A_{max} is the maximum area, which is the total roof area of 4982 m^2 for the selected building. Constraint is put on the rotor swept area of wind turbines and is shown in Equation (21):

$$A_{WT,min} \leq A_{WT} \leq A_{WT,max} [\text{m}^2] \tag{21}$$

where, A_{WT} is the area of wind turbines. $A_{WT,min}$ and $A_{WT,max}$ is the minimum and maximum area of wind turbine respectively, considered as: $A_{WT,min}$ = 5 m^2 and $A_{WT,max}$ = 8 m^2. As mentioned before, the batteries can provide energy up to SOC_{min} lower limit and can be charged before SOC_{max} is achieved, Equation (22).

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{22}$$

where, SOC_{min} = 30% and SOC_{max} = 100% (Abedi et al., 2012). The demarcation of hydrogen level is shown in Equation (23).

$$H_{2_{level-min}} \leq H_{2_{level}}(t) \leq H_{2_{level-max}} \tag{23}$$

where, $H_{2,level-min}$ is the nominal capacity of H_2-tank (P_{Tank}), and $H_{2,level-max}$ is considered 5% of the rated capacity. There are nonnegativity constraints for decision variables and energy flux Equation (24), (25).

$$0 \leq P_j(t) \leq P_{j_{max}} \tag{24}$$

$$E_j(t) \geq 0 \tag{25}$$

The maximum unmet load (UL) permitted is an input of the proposed design tool. The UL (kWh/year) is specified as the amount of energy that could not be provided by the DER system over the lifetime. The unmet load is defined as the difference between total annual load demand and energy provided by DER system. The constraint on the unmet load is provided in Equation (26).

$$UL\ (\%) \leq 0\% \tag{26}$$

5. RESULTS AND DISCUSSION

The present study explores how the usage of renewable energy resources can result in the reduction of total system costs and carbon dioxide emissions relative to a base case scenario where all the energy used by the selected building is provided through the electricity grid. Four scenarios are analyzed to measure the impact of optimizing the DER systems to design and operate residential or commercial energy systems: typical, off grid, on grid and feed-in-tariffs. Case 1: 'Typical' pertains to the fulfillment of the demand for electricity from the grid. Case 2: 'Off grid' relates to a consumer that does not take electricity from the grid but can sell electricity to grid. Case 3: 'On grid' refers to a consumer that has provision to satisfy the demand for electricity from the grid as well as from all possible renewable sources. However, excess electricity produced cannot be exported to the grid. Case 4: 'Feed-in-tariffs' corresponds to the exchange (export and import) of electricity at the same price. Figure 3 shows the yearly energy produced by solar panels and wind turbines in each case scenario. Case 1 is the reference case where all the energy requirement is provided by the electricity grid. Case 2 has almost equal contribution by solar panels and wind turbines. The yearly energy reduction by solar panels is 50% whereas by wind turbines is 41%. Cases 3 & 4 mostly favor the installation of solar panels. Energy reduction by solar panels and wind turbines is 74% and 16% respectively.

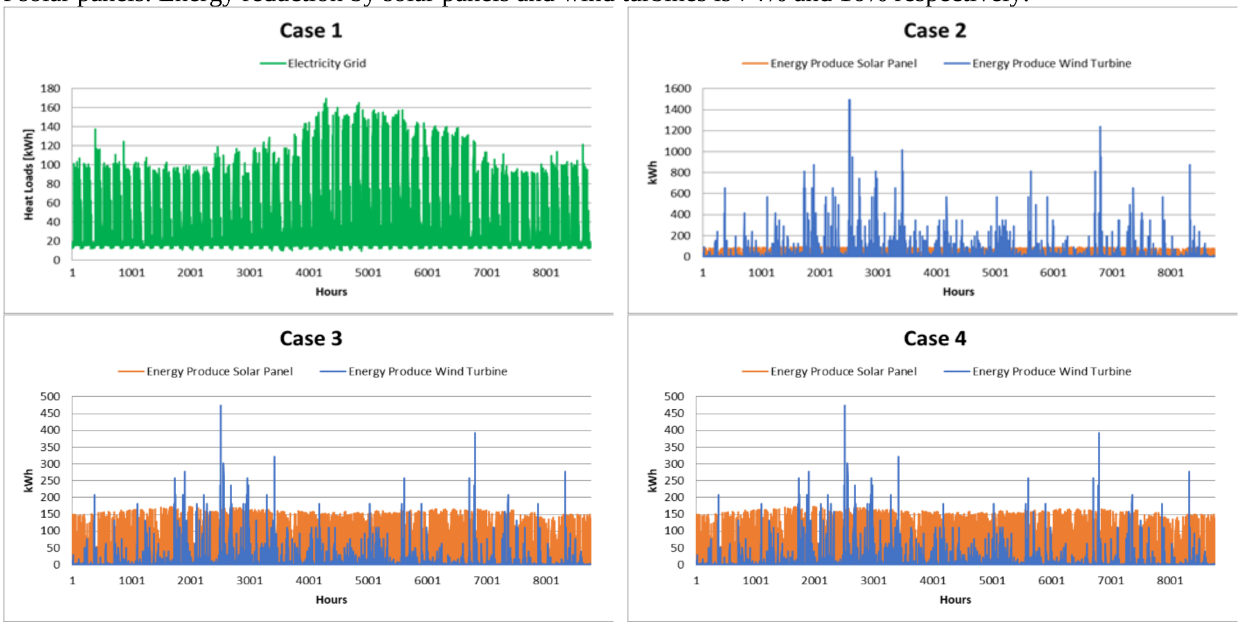
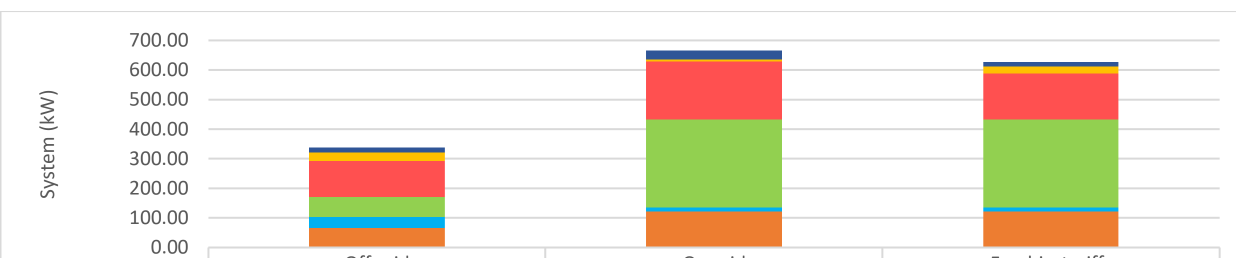


Figure 3: Energy produced by the system components

Figure 4 shows the optimal size of the system component for each case scenario. There is a 50% increase in the system total capacity for 'on grid and 'feed-in-tariffs' compared to that of the 'off grid' case scenario. The reason for the increase of the battery capacity by almost four times is that now the system cannot sell the excess energy to the grid and to accommodate any unexpected peak load requirements, the system needs to be always well equipped. This can be achieved through an increase in the storage size (battery capacity), an increase in the fuel cell capacity, or a combination of both. Indeed, 'on grid' case observes a growth in the capacity of fuel cell from 16.42 to 30.59 kW and rise in the solar panel capacity from 65 to 122 kW. Wind capacity is however decreased due to its increased installation costs. The most extreme change in the capacity is that of the battery, due to two key factors. Firstly, the solar panels and the fuel cell generate ample energy to sustain a battery charge state high enough to cover any unpredicted variation in the load demands. Secondly, the life cycle cost of increasing the capacity of battery is almost three times lesser compared to the life cycle cost of increasing the capacity of the fuel cell.



	Off grid	On grid	Feed-in-tariffs
Fuel cell	16.42	30.59	15.42
Electrolyzer	28.27	5.23	23.67
Hydrogen Tank	120.68	197.44	154.72
Battery	68.53	297.49	298.99
Wind Turbine	37.53	11.92	11.92
Solar Panel	65.72	122.81	122.81

Figure 4: System component size

Figure 5 shows the system component cost and savings in its lifetime of 25 years. The cost of electricity provided by the grid is $919,192. Both solar panels and wind turbines provide energy cost savings, which is higher than their installation costs. Therefore, it has net present savings after the studied period of 25 years. Off grid system has higher savings due to wind turbines compared to solar panels. However, both on grid and feed-in-tariffs systems have a higher savings due to solar panels. On grid storage systems have a lower life cycle costs compared to the other two cases. Interestingly, within the considered lifetime of 25 years, there is total life cycle savings of $267,815 only by the off grid scenario. There is no savings by the other two cases in the first 25 years. However, there is almost 50% decrease in the life cycle costs by the feed-in-tariffs system compared to on grid system.

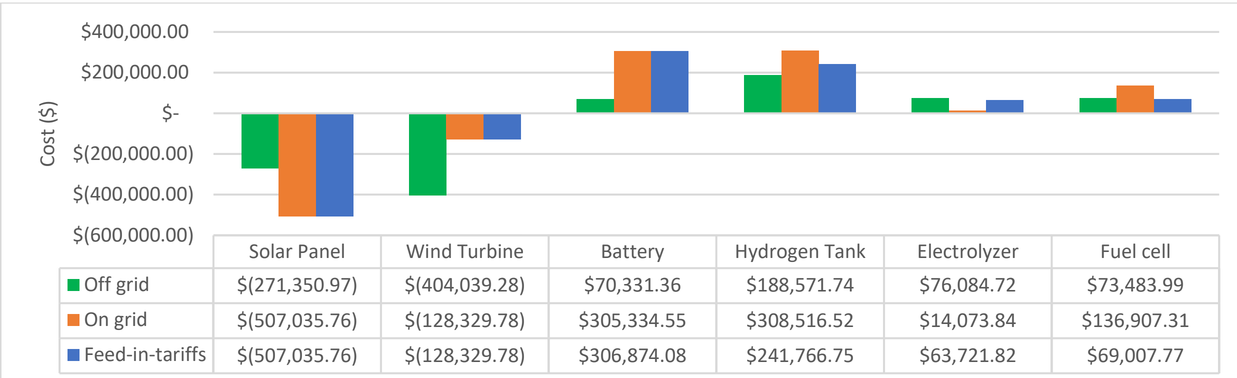


Figure 5: System component life cycle cost

Table 3 provides a summary of the results obtained through the optimization. According to the results, off grid system seems like the best option as it has the lowest levelized cost of energy of 0.053 $/kWh. In addition, it has a simple payback period of 16 years, which is better than the higher payback period of on grid and feed-in-tariffs which gives a return after additional 10 years.

Table 3: Summary of results

	Off grid	**On grid**	**Feed-in-tariffs**
Area of solar panels (m^2)	529.86	990.07	990.07
Number of wind turbines	5.77	1.83	1.83
Number of batteries	6.85	29.75	29.9
Levelized cost of energy ($/kWh)	0.053	0.090	0.082
Simple payback (years)	16.95	28.38	26.5

Even though there are no added incentives that promote the use of renewable energy, it is possible to minimize lifecycle costs and CO_2 emissions by combining today's available technologies. Uncertainty in energy production and requirement is not considered while obtaining the results. Overall, the developed tool proves to be instrumental in determining investment decisions that are resilient in terms of uncertainty in weather parameters.

6. CONCLUSION

An innovative and novel method is presented in this paper that can be used to optimize the size of a distributed energy resource system. The genetic algorithm method is utilized to minimize the objectives that include the total lifecycle cost of the system and CO_2 emission. In order to solve the multi-objective optimization problem, the developed tool used a simulation-based method. One of the key advantages of the proposed method is its easy and effortlessness execution, which results in computational efficiency. The proposed study is evaluated in a case study that includes solar panels, wind turbines, batteries, hydrogen tank, electrolyzer and fuel cell. Four scenarios were analyzed to measure the impact of planning and operating the distributed energy resources: typical, off grid, on grid, feed-in-tariffs. By comparing the four scenarios, it was concluded that the total cost was improved in all the cases, with additional cost savings in one of the them. The proposed tool can be utilized in research studies and the design of a DER system. The approach can easily be extended to heating/cooling loads as well as domestic hot water loads. The framework is developed in such a way that any number of conventional and renewable energy resources can be added to a selected building to obtain an optimized system with minimum cost and CO_2 emissions.

For future research, a sensitivity analysis can be done in order to see the effect of a certain technology based on its economic or environmental impact under different climatic conditions. Another sensitivity analysis can be performed on the developed model to analyze the sensibility of the input parameters. The analysis would be used to predict the outcome if the efficiency and cost of the system components are changed. Furthermore, a comprehensive analysis on the load, that separately takes into account the heating/cooling and electricity, can be done to generate an optimum system configuration that matches the load. Lastly, uncertainty on the availability of intermittent energy sources can be studied as well.

REFERENCES

Abedi, S., Alimardani, A., Gharehpetian, G. B., Riahy, G. H., & Hosseinian, S. H. (2012). A comprehensive method for optimal power management and design of hybrid RES-based autonomous energy systems. *Renewable and Sustainable Energy Reviews*, *16*(3), 1577–1587. https://doi.org/10.1016/j.rser.2011.11.030

Brooks, S. (n.d.). The true cost of carbon pollution. Retrieved from Environmental Defense Fund website: https://www.edf.org/true-cost-carbon-pollution

Dufo-López, R., & Bernal-Agustín, J. L. (2008). Multi-objective design of PV-wind-diesel-hydrogen-battery systems. *Renewable Energy*, *33*(12), 2559–2572. https://doi.org/10.1016/j.renene.2008.02.027

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Seyboth, K., Eickemeier, P., Matschoss, P., … Stechow, C. Von. (2011). IPCC, 2011: Summary for Policymakers. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. In *Cambridge University Press*. https://doi.org/10.5860/CHOICE.49-6309

Ekren, O., & Ekren, B. Y. (2010). Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing. *Applied Energy*, *87*(2), 592–598. https://doi.org/10.1016/J.APENERGY.2009.05.022

House, T. (2017). Quantifying the Value of a Solar Installation: Some Helpful Metrics. Retrieved from AuroraSolar website: https://blog.aurorasolar.com/quantifying-the-value-of-a-solar-installation/

Kashefi Kaviani, A., Riahy, G. H., & Kouhsari, S. M. (2009). Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages. *Renewable Energy*, *34*(11), 2380–2390. https://doi.org/10.1016/j.renene.2009.03.020

Mallikarjun, S., & Lewis, H. F. (2014). Energy technology allocation for distributed energy resources: A strategic technology-policy framework. *Energy*, *72*, 783–799. https://doi.org/10.1016/j.energy.2014.05.113

Milousi, M., Souliotis, M., Arampatzis, G., Papaefthimiou, S., Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change, … Shahsavar, A. (2019). Multi-criteria decision support system of the photovoltaic and solar thermal energy systems using the multi-objective optimization algorithm. *Energy*, *11*(March), 1–10. https://doi.org/10.3390/su11092539

Sharafi, M., & ELMekkawy, T. Y. (2014). Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach. *Renewable Energy*, *68*, 67–79. https://doi.org/10.1016/j.renene.2014.01.011

ACKNOWLEDGEMENT

We would like to acknowledge the support received from the Lyles School of Civil Engineering at Purdue University, West Lafayette, USA, in conducting the presented research work.