

Optimal Design and Intelligent Management of Hybrid Power System

Reza Sedaghati

Abstract—Given the increasing energy demand in the world as well as limited fossil energy fuel resources, it is necessary to use renewable energy resources more than ever. Developing a hybrid energy system is suggested to overcome the intermittence of renewable energy resources such as sun and wind, in which the excess electrical energy can be converted and stored. While these resources store the energy, they can provide a more reliable system that is really suitable for off-grid applications. In hybrid systems, a methodology for optimal sizing of power generation systems components is of great importance in terms of economic aspects and efficiency. In this study, a hybrid energy system is designed to supply an off-grid sample load pattern with the aim of supplying necessary energy and minimizing the total production cost throughout the system life as well as increasing the reliability. For this purpose, the optimal size and the cost function of these resources is determined and minimized using evolutionary algorithms and system efficiency is studied with real-time load and meteorological information of Kazerun, a city in southern Iran under different conditions.

Keywords—Hybrid energy system, intelligent method, optimal size, minimal.

I. INTRODUCTION

ENERGY is known as the most important and essential principle to achieve economic development in countries. Many of the energy demand for economic growth and political and social development is met by fossil fuels [1]. Today, it is a crucial issue to satisfy human energy requirements. Industrial world development, growing energy demand, limited fossil fuels resources and conserving them for future generations and preventing environmental harm associated with burning them are some factors that necessitate using renewable energies. Today, hybrid systems have become one of the most promising solutions to meet the electricity demand in different regions. In particular, the wind and solar energies are infinite, location-dependent, non-pollutant and high-potential resources to combine and generate the intermittent energy. For independent and remote systems such as radio communications systems, satellite ground stations, etc. away from a power system, hybrid energy system is preferred [2], [3]. On the one hand, lack of global electrical network in remote areas, high-cost building of new transmission lines due to long distances, the increased rate of electricity consumption and a large number of distant consumers are the biggest problems facing power companies. Ever-growing energy demand, non-renewable nature and high costs of fossil fuels,

environmental concerns and such problems have aroused an interest in renewable power generation technologies. Solar and wind energies are considered as the most important renewable resources with high potential to become green energy resources in the near future due to high efficiency, no emissions and flexible structure. A hybrid energy system can be formed by combining several energy resources including photovoltaic, wind generators, fuel cells, diesel generators, gas turbines and micro-turbines [4], [5]. Despite these resources, solar cell units and wind generators are widely used to bring the power with remote areas. Given that the characteristics of these systems supplement each other well, they are usually combined with each other to use. Since this energy is clean and renewable, numerous organizations and countries are interested in using it and carry out researches on this subject area.

Dramatic increase in energy demand, non-renewable nature of fossil fuels, high cost of fossil fuels, environmental concerns and such problems are the main factors of renewable energies development. These energies are able to produce clean and ecofriendly energy and reduce fossil fuels use. To achieve economic goals, hybrid energy systems are normally used to supply global off-grid consumptions. These systems are mainly applied in areas where transmission network expansion is not economically justified due to the high price of land and geographical constraints of the region [6].

In order to diversify resources supplying the energy, renewable systems are applied in the form of power plant. Integrating and combining several models of renewable systems as a common and hybrid power plant, a variety of resources can be used in the renewable systems to provide necessary energy for different regions. In this method, the energies produced from resources such as wind, sun, biomass, hydrogen etc. are combined with each other, the resulting electrical energy is feed to common network, and the systems are assigned to categories with different climatic conditions. Solar and wind energies are the most important renewable resources. That is why systems generating energy by wind generator (WG) and photovoltaic (PV) have been developed dramatically [7]-[9]. Fuel cell (FC) has the high potential to become a green energy resource in the near future due to high efficiency, no emissions and flexible structure [10].

The study aims to evaluate the performance and management of hybrid systems in off-grid applications. It takes into account economic factors and system reliability in hybrid system dimensions optimization, and applies a comprehensive strategy to the system according to the importance of energy management among available resources.

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Therefore, a performance-based method is given to determine the optimal dimensions for hybrid energy systems in this study. Considering large dimensions and complex constraints of hybrid energy systems, there have been many simplifications in the extensive and various researches on this filed. The study considers the profile of power demand for consumers and real-time weather data, as well as constraints such as the reliability of hybrid energy system and environmental problems to solve optimization problem of these systems dimensions.

II. HYBRID RENEWABLE SYSTEM ENERGY MANAGEMENT

Energy is a fundamental aspect to people's life, and is essential not only for individuals but also for various sectors. It can be supplied from various resources which can be divided into two categories; renewable and non-renewable. Typical examples of non-renewable energy sources are petroleum, coal, and natural gas. As for renewable sources, these include energy generated from wind, solar, wave, geothermal, biomass and hydro. Both renewable and non-renewable energy sources can be used to produce secondary energy sources including electricity and hydrogen.

The term hybrid energy system refers to those applications in which multiple energy conversion devices are used together to supply an energy requirement. These systems are often used in isolated applications and normally include at least one renewable energy source in the configuration. Hybrid energy systems are used as an alternative to conventional systems, which typically are based on a single fossil fuel source.

A Power Management Model (PMM) [11]-[13] is a combination of mathematical models, block diagrams and technical requirements or instructions that are defined in order to create a logic operation of a Hybrid Energy System (see Fig. 1).

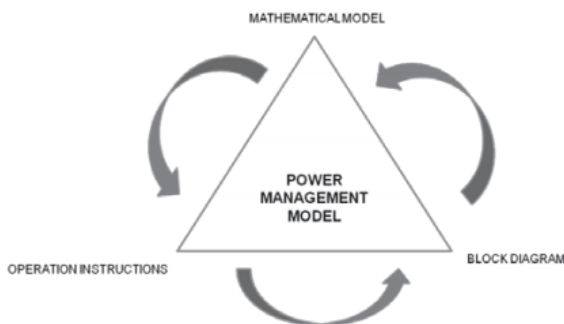


Fig. 1 PMM components interaction process

A PMM allows the coordination between different energy sources, such as solar cells, electrolyzers and FC, to maintain the continuous feeding to an electrical critical DC load.

- PMM has to be considered in order to determine when the various components of the system will be used.
- PMM has three components (see Fig. 2): Mathematical model, block diagram and set of system operation instructions.

- PMM has an effect on hybrid energy system operating cost.
- PMM principles of operation are the continuous feeding of the load and the continuous energy flow among energy sources.

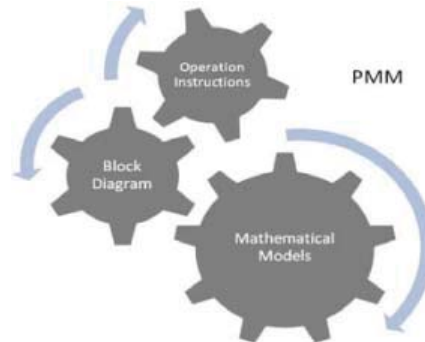


Fig. 2 PMM - main components

With the rapid growth and challenges of power generation, distribution, and usages, renewable energy technologies can play an important role in future power supply due to increased awareness of environmental pollution. In the case of power supply system to remote and isolated communities, a renewable energy based stand-alone power system can be a particularly attractive cost-effective solution, as grid extension is often impractical due to economic and technical constraints.

Diesel generators are most commonly used as a stand-alone power supply system application to isolated communities for their reliability, cheap installation, ease of starting, compact power density and portability [13]. However, rising fuel prices make them very expensive to run. Moreover, they cause significant environmental pollutions. In most remote and isolated areas, renewable energy sources such as wind and solar are available, which can provide clean cost-effective power. However, due to the intermittent nature of renewable energy sources, hybrid combinations of two or more energy sources along with energy storage can improve reliability and ensure a continuous and cost-effective power supply.

Different generation sources may operate in tandem to achieve higher energy efficiency and improve system performance. As an example, wind and solar power can complement each other on daily basis. Integration of battery or super-capacitor storage systems can improve transient stability of a fuel cell and wind turbine based hybrid power system in the event of wind and load changes [14].

In renewable energy-based hybrid power system applications, energy storage is considered as an integral part of the system. Energy storage can improve transient stability of the system when wind and load variation occurs [15]. Most importantly, they are used for load leveling and peak shaving applications [11]. However, proper technology selection, operation and control strategies, structure of the hybrid power system, and generation unit sizing are also vital to construct a robust renewable energy based hybrid power supply system.

A well-defined framework of a hybrid system is vital, as various energy sources may have different operating characteristics. In an optimal framework, the renewable energy sources, energy storage, and loads are integrated and capable of operating autonomously as a unit. A robust system should also have a “plug-and-play” capability which renders the system capable of integrating any number of devices without system re-configuration. There are various ways to integrate different energy sources and storage to form a hybrid power system. Among them, dc-coupled, ac-coupled and hybrid-coupled are the most popular options, which outlined as below:

A. DC-Coupled Systems

In a DC-coupled system, all renewable energy sources are connected to a dc bus either directly or through appropriate power electronic converters. A block diagram of the system is shown in Fig. 3. This system can be connected to the dc loads through appropriate dc-dc converter, ac loads through a DC-AC converter or utility grid through a bi-directional DC-AC converter. The system is flexible and can be connected to an AC load of 50/60 Hz frequency. The DC-coupling scheme is very simple and is not required to be synchronous with the AC system. However, a DC-coupled system suffers from various weaknesses. For example, if the system converter connecting the utility grid with the bus is out of service, the whole system will not be able to supply AC power. To rectify this, several inverters can be connected in parallel. As such, synchronization of output AC voltage and proper power sharing are required to achieve a desired load distribution [15].

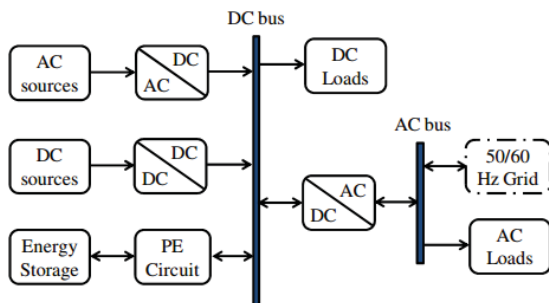


Fig. 3 Schematic diagram of DC-coupled hybrid energy system

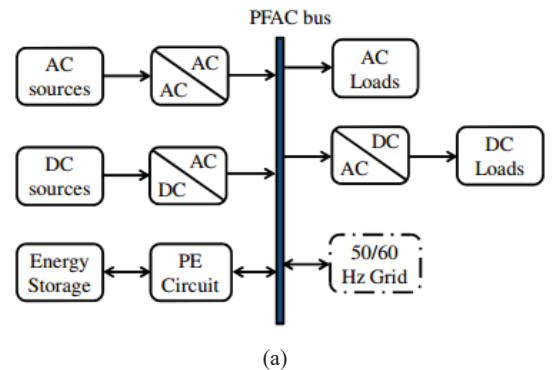
B. AC-Coupled Systems

An AC-coupled system can be divided into two categories: power frequency AC-coupled (PFAC), and high frequency AC-coupled (HFAC) systems. The PFAC coupled system is shown in Fig. 4 (a), where the different energy sources are integrated through their own power electronic interfacing circuits to a power frequency ac bus. In this arrangement, coupling inductors are required between the power electronic interfacing circuits and power frequency ac bus to achieve the desired power flow management.

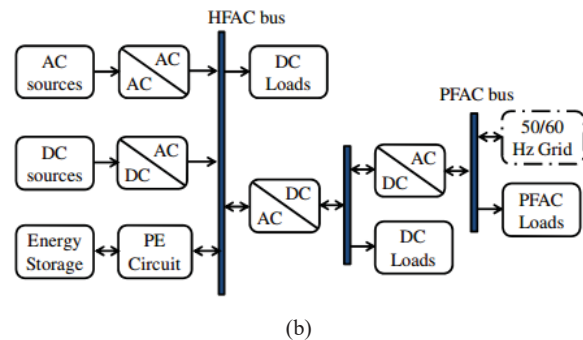
The HFAC system is shown in Fig. 4 (b), where different energy sources are coupled to a HFAC bus in which HFAC loads are located. This application is mainly used for HFAC

loads (e.g., 400 Hz) such as airplanes, vessels, submarines and space stations.

In both PFAC and HFAC systems, DC power can be obtained through an AC-DC converter. The HFAC may also include a PFAC bus and utility grid through an appropriate AC-AC and/or AC-DC converter, where regular AC loads can be connected.



(a)



(b)

Fig. 4 Schematic diagram of AC-coupled hybrid energy system

C. Hybrid-Coupled Systems

In hybrid-coupled system as shown in Fig. 5, various DG sources are connected to the DC or AC buses of the hybrid system. In this application, some energy sources can be implemented directly without the use of a power electronic interfacing system. As a result, the system can operate with higher efficiency and reduced cost. However, control and energy management can be more complicated than with DC-coupled and AC-coupled systems.

Different coupling schemes have their own appropriate applications. If the major generation sources generate DC power and there is a substantial DC load in the system, a DC-coupling system is preferable. On the other hand, if the main power systems are AC with substantial AC loads, an AC-coupled system is preferred. If the major power generation system is a combination of ac and dc power, then hybrid coupled system is the best.

The rapidly improving green technologies allow renewable energy generators to harness renewable sources with high efficiency. Although the advanced technologies of the renewable energy generators and power conversion units are able to improve the amount of energy yields, the energy that is

available to consumers is determined by the energy flow path in a system configuration that is related to the arrangement of components in a hybrid power system. There are a number of approaches in connecting the system components. Generally, these connections are broadly classified as series and parallel configurations.

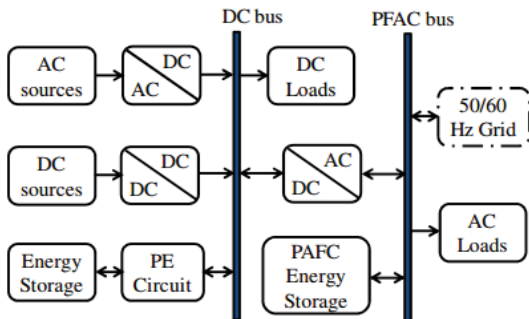


Fig. 5 Schematic diagram hybrid-coupled hybrid energy system

Connection of the components in a series configuration is illustrated in Fig. 6. This configuration is only applicable to the DC bus system; therefore, it is also referred to as a DC coupled system [14], [15]. In a series configuration, the inverter and the battery bank have to be sized to meet the peak load demand. Power from the PV generator and the diesel generator has to go through the battery bank before supplying the load demand. Due to this reason, the battery bank is cycled frequently, which can result in shorter battery life span. Moreover, cycling of the energy from the PV and diesel generators also results in low overall system efficiency [16].

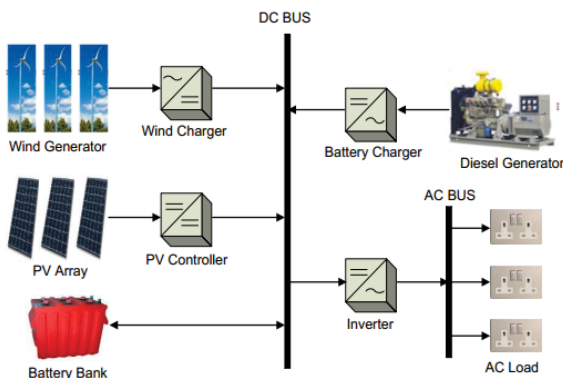


Fig. 6 Series hybrid power system configuration

The parallel configuration is appropriate for DC, AC or mixed bus system designs [14]. Figs. 7 and 8 illustrate two alternative parallel hybrid power system configurations. One of the advantages of the parallel configuration over the series configuration is that the energy sources are connected in a way that the generators can supply the load demand separately. When the generators are operating in parallel with the renewable energy generator, energy can be supplied to the loads directly without cycling through the battery. Only the excessive energy generated will be stored for the purpose of

“peak shaving”, i.e. to supply the loads that exceed the capacities of the combined sources; for instance, during the peak load demand that usually occurs in the evening. In terms of controllability, the parallel configuration is flexible, where an advanced system level control strategy can be implemented to dispatch and control the dispatchable components [17].

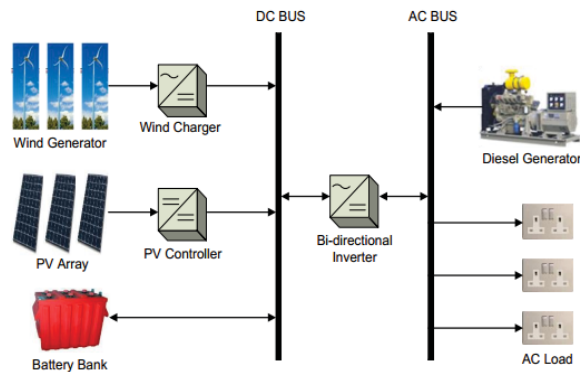


Fig. 7 Parallel hybrid power system configuration

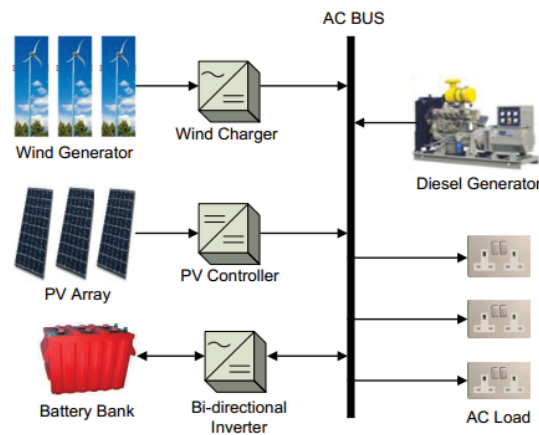


Fig. 8 AC coupled system, an alternating parallel configuration

As seen from the previous system configurations, a fuel-powered diesel generator, (usually it is a constant speed diesel generator (CSDG)), is required to operate along with the renewable energy generator to provide reliable power supply. However, there are some drawbacks associated with the use of CSDG. Traditionally, a CSDG is sized to meet the peak load demand that lasts only for a short period of time in daily operation [18]. As the name implies, the CSDG runs at constant speed and has to be operated above a minimum power level around 40% to 50% of the CSDG's power rating. This operation mode is recommended by most of the manufacturers to relieve engine problems such as: hydrocarbon build-up, as well as glazed piston and cylinder walls. Prolonged low load operations of the engines at the constant rated speed contribute to premature aging of the engine and inefficient burning of fuel [19]. In addition, the rigid operating range of a CSDG also reduces the flexibility of the system level control.

III. SYSTEM SPECIFICATIONS AND DIMENSIONS

Fig. 9 shows a block diagram for hybrid system including wind turbine, PV array, FC and electrolysis along with the reformer and battery. Wind turbine and PV array are considered as the main energy generators and FC and battery as energy storage and backup system. Using power electronic converters as an intermediary between the components is also one of the interesting points of the system [8]. The energy generated by wind turbine and PV array is sent to consumers through a power electronic inverter and electrical energy demand is met. The excess energy is stored in the lead-acid batteries or consumed by electrolysis to produce hydrogen. The hydrogen obtained from the process is stored in the hydrogen storage tank to be converted into electricity by the FC as needed.

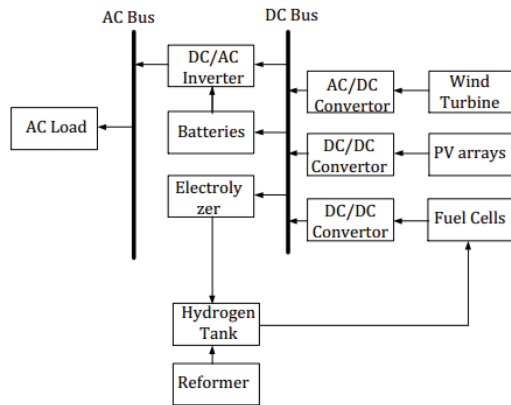


Fig. 9 Block diagram of hybrid system under study

IV. MODEL OF HYBRID SYSTEM COMPONENTS

In order to optimally design and manage the energy as well as visualize system operation under different conditions, it is necessary to gather the necessary information about the components structure. Hybrid system under the study consists of wind turbine, photovoltaic cell, fuel cell, electrolysis, battery and converter [20].

A. Wind Turbine Model

The wind turbine system converts the energy available in wind into electrical energy. Here, BWC Excel-R/48 wind turbine designed by Bergey Company for home applications is used [21]. The rated power and output voltage of turbine are 5.7 kW and 48 V, respectively. Fig. 10 shows the characteristic curve for wind turbine under the study. The output power of wind turbine is calculated by (1):

$$P_w(t) = \begin{cases} 0 & V_w \leq V_c, V_w \geq V_f \\ P_m \left(\frac{V_t - V_c}{V_r - V_c} \right)^3 & V_c \leq V_w \leq V_r \\ P_m & V_r \leq V_w \leq V_f \end{cases} \quad (1)$$

where P_w denotes the output power of the wind turbine; P_r is the rated power per turbine, V_w , V_c , V_t and V_r are wind velocity, down-cut velocity, up-cut velocity and rated velocity of turbine, respectively. Other features and parameters of wind turbine used in modeling are presented in Table I.

TABLE I
TECHNICAL SPECIFICATIONS OF WIND TURBINES

Rated power	7/5W
Installation costs	19400US\$
Change costs	15000US\$
Maintenance costs	75US\$/yr
Lifetime	20yr

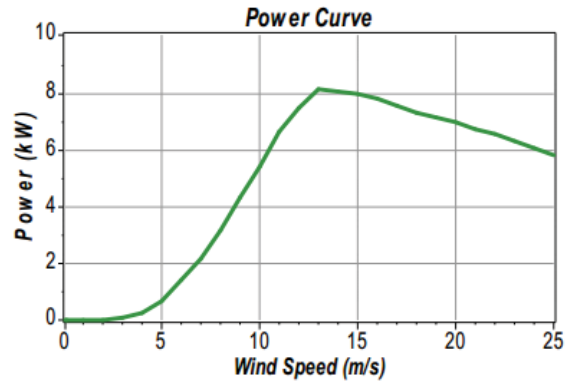


Fig. 10 Block diagram of hybrid system under study

B. Photovoltaic Model

PV cells convert sunlight energy into electrical energy DC. The maximum power point position of PV generator specifications depends on solar radiation and cell temperature. The output flow is a function of cells technology-specific radiation, temperature, wind velocity and coefficients [22]. Today, these cells are generally prepared by Silicon material and the required Silicon is made of sand that is abundant in desert regions of the country. There are various equivalent electric circuit models of PV cell that the most common structure is related to the single diode model, describing electrical behavior of p-n junction and having the least number of parameters. Fig. 11 shows equivalent circuit of PV cell. Power generated by PV is given by (2):

$$P_{pv} = \frac{G}{1000} \times P_{pv, rated} \times \eta_{MPPT} \quad (2)$$

where G is radiation level in watts per square meter. P_{pv} and η_{MPPT} respectively denote the rated power of each PV panel and the efficiency of converter DC/DC in a PV panel. Technical specifications of solar modules are represented in Table II.

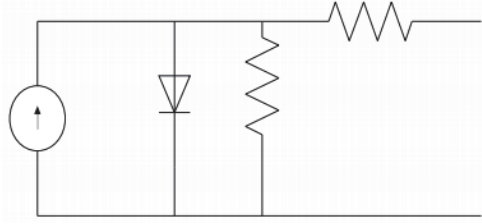


Fig. 11 Equivalent circuit of a solar cell

TABLE II
TECHNICAL SPECIFICATIONS OF SOLAR MODULES

Rated power	1W
Installation costs	7000US\$
Change costs	6000US\$
Maintenance costs	20US\$/yr
Lifetime	20yr

C. FC Model

FC is one of the novel technologies. It is an ecofriendly resource and converts the energy with a high efficiency. It seems that it can become a good alternative to combustion processes of fossil fuels especially in distributed energy generation systems in the twenty-first century due to rapid technological advances [23]. FC usage is considered a turning point in electrical energy generation industry, because it directly generates electricity through an electrochemical reaction and without the need for combustion and has special advantages such as low pollution and little noise in addition to high efficiency and energy generation in small and large scale. FC can be considered as an electrical energy supply battery which is capable of generating electrical energy as long as the fuel is supplied. Here, PEM-type FC is used. This kind of FC works with hydrogen under normal conditions (temperature, 30-200 °C; atmosphere pressure 1 and has an electrical efficiency of approximately 50%. FC power is considered to be 400 W.

D. Electrolyser Model

Electrolysis is a tool generated by water, hydrogen and oxygen decomposition. On-grid electrolysis can be considered as non-linear DC load. In this study, electrolysis is used to supply the energy needed for FC and dump the load. Alkaline-type technology is employed in electrolysis. The electrolysis uses the daily excess energy of hybrid system and supplies the hydrogen needed for FC. Electrolysis power is obtained from (3):

$$P_{\text{Electrolyser}} = P_{WG} + P_{PV} - P_{Load} \quad (3)$$

E. Batteries Model

Lead-Acid battery is used in this study. It has a big advantage over other similar batteries in terms of high efficiency, low cost and low self-discharge (less than 5% per month). Heavy weight is the main disadvantage which is negligible in stationary systems. The input power of battery can be positive or negative according to the charge or discharge state. Battery power can be obtained from (4):

$$P_{Bat} = P_{WG} + P_{PV} - P_{FC} - P_{Load} \quad (4)$$

Technical specifications of electrolyser, FC and battery are represented in Table III.

TABLE III
TECHNICAL SPECIFICATIONS OF ELECTROLYSER, FC AND BATTERY

FC	
Technology	PEMFC
Power	500W
Efficiency	50%
Operating temperature	80°C
Capital cost	8\$/w
Placement cost	6\$/w
Lifetime	5000 hour
Electrolyser	
Technology	Alkaline
Rated Power	500W
Efficiency	74%
Placement cost	20\$/w
Lifetime	20 hour
Battery	
Technology	Lead-Acid
Capital cost	20\$/KWh
Lifetime	5 hour

V. THE RELIABILITY MODEL OF LPSP

Because energy generation is profoundly influenced by the characteristics of solar radiation and discontinuous wind velocity, the analysis of power reliability is considered as an important step in hybrid systems design [10], [23]. In this study, the LPSP technique is used. A reliable electric power system has sufficient electric power to meet the load demand during a certain period. In other words, it has little LPSP power outage. LPSP is a possibility where power supply is insufficient and hybrid system cannot meet the load demand. LPSP amount is calculated at the time interval ranging from zero to T by (5):

$$LPSP = \frac{\sum_{t=0}^T \text{Power failure time}}{T} = \frac{\sum_{t=0}^T \text{Time}(P_{\text{available}}(t) < P_{\text{eede}}(t))}{T} \quad (5)$$

where T is hourly meteorological data input. The power outage is defined the time when the load is not supplied. When the power generated by PV-wind system is insufficient and battery bank storage has been finished, the necessary power for the load can be expressed as (6):

$$P_{\text{needed}} = \frac{P_{ac_load}(t)}{\eta_{\text{inverter}}} + P_{dc_load}(t) \quad (6)$$

The available power can be expressed by PV-wind hybrid system along with battery storage system.

$$P_{\text{available}}(t) = P_{PV} + P_{WT} + E_{BAT} \quad (7)$$

For a given amount of LPSP and a defined period, many configurations can technically provide the reliability requirements to supply power.

VI. GENETIC ALGORITHM

Genetic algorithm (GA), as its names suggests, is an optimization procedure inspired by the biological process of evolution and the survival-of-the-fittest concept, formally introduced by Holland in the 1970s [24], [25]. It is a global optimization technique and is derivative-free, and thus can be easily applied to both continuous and discontinuous functions. The algorithm is based on the evaluation of the objective function at a set of points within the function's variable space, which is usually first chosen randomly within the search region. Such feature allows the algorithm to be less vulnerable to local optima, and is an excellent method to solve global optimization problems.

The algorithm begins with generating a random population in the range of the optimization variables, and uses the binary encoding procedure to represent each variable as a string of binary digits. The generated variables are termed individuals, which contain a collection of genetic traits or genotypes, and are referred to as chromosomes [26]. The genotypes are represented as strings of binary digits, or genes in GA terminology. The objective functions using individuals are first evaluated and the result is called the fitness of the individuals. A set of genetic operators, such as selection, crossover, and mutation are then applied to the population. Selection is a process in which individuals are copied based on their fitness values, where highly fit individuals will have a higher number of offspring in the succeeding generation. Crossover is then applied by combining successful individuals by exchanging equivalent lengths of their chromosomes, where the two strings from the reproduced population are mated randomly. Finally, mutation is performed by picking a random chromosome and flipping a gene randomly. In essence, crossover represents searching within the local region, while mutation explores the global space to avoid being trapped in a local optimum. The fitness function of the individuals is then evaluated, and the process is repeated until the best fitness is obtained or the maximum generation is reached [27].

GA is a method that is based on natural selection. According to the natural selection method, the weak and unfit species within their environment face extinction, consequently, the strong species have a greater opportunity to pass their genes to the next generation. In GA, population is termed as a collection of individual (or chromosome). Alternately, the individual is a solution vector out of the population. The individuals are made of genes, where the genes are normally binary type. The GA schemes do not require gradient information, and they are effective regardless of the nature of the objective functions and constraints. They gather information from previous generations and random numbers to evaluate and improve a population points instead of single point at a time. Thus, GAs can sample the search space widely and efficiently. They have turned out to be

powerful search tools for solving numerous optimization problems, especially in the global optimization perspective. Fig. 12 demonstrates the operations of GA which are explained below.

A. Initial Population

Fig. 12 demonstrates at initial, a population of N_g size is randomly generated in the feasible space. The number of individuals, i.e., the population size, remains unchanged throughout the process of GA. The accuracy of the optimal solution depends on both the size of population and the number of generation. The double vector representation instead of binary one is used for chromosome codification to guarantee mutation coherence [28], [29].

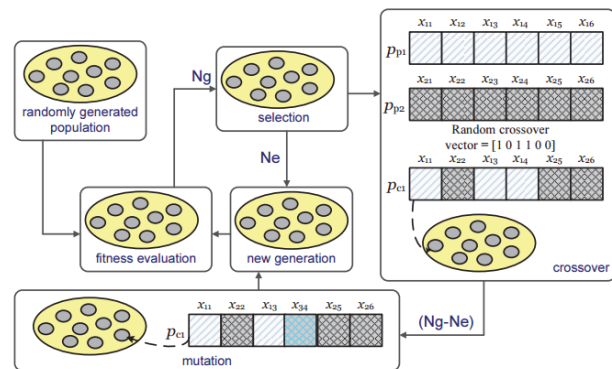


Fig. 12 Diagram of GA and operation

B. Fitness Evaluation

Fig. 12 further illustrates that each population group is utilized to evaluate the objective function. Then, a value on each individual solution is assigned that gives a measure of the solution quality. The scaling of objective function is done by assigning a rank to each individual solution. In this process, the best individual, i.e., the minimal function value, receives the maximal fitness value with greater chance for survival and vice versa.

C. Selection

After completing the fitness evaluation, individuals from the population are selected pairwise for genetic operations and thus create the offspring/child population. In this study the stochastic uniform probabilistic selection is used in order to attain the individual's selection probability proportional to the individual's fitness. The process ensures that the high quality solutions will be selected many times and become parents of many offspring. Alternately, the low quality individuals will not contribute much for generating offspring. Usually the best selection schemes are designed to maintain diverse population. The other selection process that does not take part in the offspring creation process, rather than directly copied to the next generation is called elitism. The elitism scheme preserves the best solutions for the next generation. By introducing elite count, the numbers of individuals with best fitness values in the current generation are guaranteed to survive to the next

generation. Fig. 12 illustrates that N_e are the number for elite count.

D. Crossover or Recombination

Fig. 12 shows the crossover step of GA that starts just after selection. Crossover generally produces new individuals in combining the information of two individuals, called parents. The parents are selected based on aforementioned selection process so that the offspring are expected to inherit good genes. In this study, the scattered crossover is utilized for crossover operation. Fig. 12 shows the scattered process creates a binary vector and then the process selects the genes from the first and second parents when the vector is a 1 and 0, respectively, in order to diversify genes in the expected offspring. This crossover scheme is applied iteratively until generating the desired number of offspring. According to Fig. 9, if the elitism selection is N_e , the crossover scheme will produce $N_g - N_e$ offspring [30].

E. Mutation

The mutation scheme introduces random changes in the genes of the individual. Fig. 12 shows the changes of gene x_{14} occurs to x_{34} at random. For mutation operation, the Gaussian scheme is employed in this study. Generally, mutation fraction is kept at low so that the new individual that is created by mutation does not vary a lot from the original one [31]. It is observed earlier that crossover converges the offspring to similar type, whereas mutation reintroduces genetic diversity in the individual. Thus, mutation GA helps the search for global optimization. The flowchart of GA is shown in Fig. 13.

VII. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

Swarm intelligence (SI) is based on the collective behavior of decentralized, self organized systems. It may be natural or artificial. Natural examples of SI are ant colonies, fish schooling, bird flocking, bee swarming and so on. Besides multi-robot systems, some computer program for tackling optimization and data analysis problems are examples for some human artifacts of SI. The most successful SI techniques are PSO and Ant Colony Optimization (ACO) [31]-[32]. In PSO, each particle flies through the multidimensional space and adjusts its position in every step with its own experience and that of peers toward an optimum solution by the entire swarm. Therefore, the PSO algorithm is a member of SI.

The PSO is a novel population based stochastic search algorithm and an alternative solution to the complex non-linear optimization problem. The PSO algorithm was first introduced by Dr. Kennedy and Dr. Eberhart in 1995 and its basic idea was originally inspired by simulation of the social behavior of animals. It is based on the natural process of group communication to share individual knowledge when a group of birds or insects search food or migrate and so forth in a searching space, although all birds or insects do not know where the best position is. But from the nature of the social behavior, if any member can find out a desirable path to go, the rest of the members will follow quickly [33].

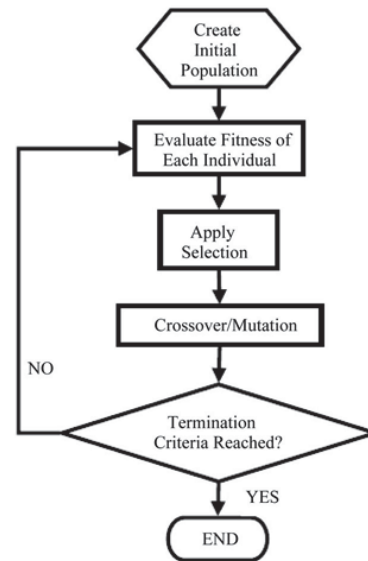


Fig. 13 Basic GA Flowchart

The PSO routine requires parameters including limits on feasible design space in restricted domain problems as well as operational parameters for the method itself. The specific variant used in this basic PSO implementation is the inertia weight method which applies a velocity reduction factor to the previous velocity at each update. This is the simplest PSO variation and allows some velocity limitation without fully stifling the acceleration offered by the PSO. The factor was chosen to be very small in this study when compared with other PSO variants due to the desire for a more complete exploration of the local spaces after initialization. The alternate velocity restricting variation, the constriction factor, would have reduce the impact of new information to the particles and is more complex without providing clear benefits to this problem.

The PSO algorithm basically learned from animal's activity or behavior to solve optimization problems. In PSO, each member of the population is called a particle and the population is called a swarm. Starting with a randomly initialized population and moving in randomly chosen directions, each particle goes through the searching space and remembers the best previous positions of itself and its neighbors. Particles of a swarm communicate good positions to each other as well as dynamically adjust their own position and velocity derived from the best position of all particles. The next step begins when all particles have been moved. Finally, all particles tend to fly towards better and better positions over the searching process until the swarm moves to close to an optimum of the fitness function $f : R^n \rightarrow R$.

The PSO method is becoming very popular because of its simplicity of implementation as well as ability to swiftly converge to a good solution. It does not require any gradient information of the function to be optimized and uses only primitive mathematical operators [34].

As a heuristic method, of course, the PSO cannot guarantee the location a global optimum within the design space, although it does perform well on problems with non-differentiable space and with convoluted response variables. PSO is just one example of a group of methods, classified as evolutionary methods, along with the GA, which has been commonly applied to internal combustion engine optimization [34], [35]

Optimization of internal combustion engine operating parameters is a very complex and difficult problem. Heuristics in general, and specifically evolutionary methods, are an efficient way to optimize parameter selection within a particular test environment with such complexity [36]. The PSO and GA have both been shown to be effective methods for optimizing combustions systems, especially with a high number of variables in the design space and convolutions in the response characteristic which cannot be optimized with gradient search techniques [32].

PSO has been used extensively since its emergence and many variations have been developed for specific applications and classes of problems [33]. Generalizations of the “social intelligence” factors have been developed into more modern methods such as neural network development and advanced topology structures within the PSO but these have tended to focus on well-studied test functions. Modern advancements in heuristic optimization have focused on generalized methods, computational systems, and standard test batteries, which have been widely used to evaluate the performance of optimization routines. On one hand, we want the method to perform well on a wide range of problems, while on the other hand, performance in unrelated realms may actually serve as a detriment to the specific application, as illustrated by the “no free lunch” theorem [35].

In experimental application an operator or designer has at hand a large amount of problem specific knowledge and potentially previously accepted test methods. The basic PSO algorithm is generally devoid of preference toward problem-specific knowledge and is widely applicable to almost all problem types, be they continuous or discrete, global or localized, etc. As applied to engine studies the basic PSO has performed well enough to be considered effective, though the PSO does have some drawbacks. Drawbacks of the general PSO method include its single-objective arrangement, a likelihood of premature convergence by clustering in a local optimum, the inability to make vast leaps to isolated regions of the feasible design space, and stagnancy in late stages. The advantages of the PSO method include rapid discovery of the approximate optimum, minimal objective evaluations when compared to other evolutionary algorithms, few tuning parameters, and relative simplistic methodology [27], [32]. The particle swarm algorithm is simple in construction and implementation requiring only a few lines of code to operate.

$$X_{i+1} = X_i + V_{i+1} \quad (8)$$

$$V_{i+1} = \alpha V_i + C_1 R_1 (P_{best,i} - X_i) + C_2 R_2 (G_{best} - X_i) \quad (9)$$

The PSO algorithm uses two weight parameters to balance the individual and social confidence factors for the particle while stochastic elements are multiplied to those weights which vary the interest of the particles at each iteration. Another weight is used to either reduce the current velocity or reduce the impact of the previous velocity factor. These are called the constriction factor and the inertia weight respectively and in practice only one is applied, but almost all variations of the PSO use one or the other to prevent velocities of particles far from the global best from accumulating too much velocity and diverging [14]. This basic PSO has been used successfully in combustion research and is the simple variation used in this study. Much work has been done on many PSO variations as well as parameter selection for the velocity reduction factor, social interest factor, and individual interest factor [11]. Such analysis is beyond the scope of this study and to emphasize the benefits of the methodology proposed no work beyond simply choosing well respected values for these parameters. Substantial work exists on not only the choice of the parameters themselves but on how to optimize even those parameter choices (a realm of optimization called meta-heuristics) [3]. Furthermore, the parameters were kept constant even if an improvement could be realized because the ultimate goal of the research presented here is to validate the construction and novel application of the method rather than compare the absolute performance of each method independently after meta-optimization of the optimization itself. The flowchart of PSO is shown in Fig. 14.

Basic PSO may not be suitable for all type of problems. For the application of PSO in the different types of problems, many variants of the original algorithm have been proposed. Depending on the variations in the constants or solution technique, there are different types of PSO have been proposed.

A. Canonical PSO

In [33] included a new kind of technique into the PSO. Combination of several parameters determines the convergence properties of the algorithm. To control the convergence properties of the particles they introduced a “Constriction Factor (X)” into the basic PSO. After introducing the Constriction Factor (X), the velocities update can be expressed by (10):

$$V_{i+1} = X (V_i + C_1 U_1 (p_{best,i} - X_i) + C_2 U_2 (g_{best} - X_i)) \quad (10)$$

where $X = 2k / (2 - \varphi - \sqrt{\varphi^2 - 4\varphi})$. Here c_1 is the “cognitive parameter” and c_2 is the “social parameter”, k is a random number which varies from 0 to 1, i.e. $k \in [0,1]$, $\varphi = c_1 + c_2$ and φ should be greater than 4.

B. Time Varying Inertia Weight PSO (TVIM-PSO)

In this case [32], the velocity update rule can be expressed by (11):

$$V_{i+1} = \omega(t)V_i + C_1 U_1'(pb_i' - X_i') + C_2 U_2'(gb' - X_i') \quad (11)$$

Generally, time varying inertia weight, $w(t)$ always varies linearly from an initial value to final value. In most cases, both the parameters c_1 and c_2 are set to 2.

C. Stochastic Inertia Weight PSO (STO-PSO)

In the basic PSO, particle influences Russell Eberhart and Yuhui Shi proposed another variant into PSO [35]. This technique was first introduced by them. In this technique, according to a uniform distribution in the range [0.5, 1.0], the inertia weight is randomly selected. This range was inspired by Maurice Clerc and James Kennedy's constriction factor. In this version, both acceleration coefficients c_1 and c_2 are set to 1.494 [27]. Although this variant was originally proposed for dynamic environments, it has also been shown to be a competitive optimizer for static ones. In Stochastic variant a new update rule and re-produce strategy has been evolved, and it can convergent onto global optima with probability one. However, due to the large global search capability, the exploitation capability is not well.

D. Fully Informed PSO (FI-PSO)

Mendes et al. [28] introduced this technique first. In the basic PSO, particle influences only from best particle. But in this version, particle uses information from all its topological neighbors. This variant is based on the fact that Clerc and Kennedy's constriction factor does not enforce that the value φ should be split only between two attractors. For taking information from all neighbors, φ (where $\varphi = c_1 + c_2$) is decomposed in $\varphi_k = \varphi / |N|$, $\forall k \in N$, where N is the neighborhood of the particle. If we consider this terminology, then the new velocity update can be expressed by (12):

$$V_{i+1} = X[V_i + \sum_{k \in N} \varphi_k \omega(k) U_k(p_k - X_i')] \quad (12)$$

where $W(k)$ is a weighting function.

E. Time-Varying Acceleration Coefficients PSO (TVAC-PSO)

In the standard PSO method, information of each particle in the swarm are recorded by different variables. They are guided by personal influence as well as social influence which depend on cognitive parameter (c_1) and social parameter (c_2) respectively. These two parameters are called acceleration coefficients. Therefore, proper control of these two components is very important to find the optimum solution accurately and efficiently. In this technique, we vary the acceleration coefficients (cognitive and social parameter) with respect to time or iteration. At the beginning, we select large cognitive component and small social component. And in the latter stage, we select small cognitive component and large social component. Variation is added only in the terminal iterations to prevent premature convergence. Due to this type of selection, particles are allowed to move around the search space, instead of moving toward the population best at the

beginning and on the other hand, particles try to converge to the global optima in the latter part of the optimization. TVLPSO has good potential in finding better solutions [33].

F. Self-Organizing Hierarchical PSO with Time-Varying Acceleration Coefficients (HPSO-TVAC)

This technique was first introduced by Ratnaweera et al. [28]. He drops the velocity term from the right side of the equation that is described on time varying inertia weight context. In this technique, they proposed the new velocity update can be expressed by (13):

$$V_{i+1} = C_1 U_1'(pb_i' - X_i') + C_2 U_2'(gb' - X_i') \quad (13)$$

But the variation in the acceleration coefficients is similar to TVAC-PSO i.e. c_1 varies from 2.5 to 0.5 and a c_2 varies from 0.5 to 2.5 according to (13). During the velocity calculation, if a particle's new velocity becomes zero (in any dimension), then in that condition, that velocity is reinitialized to some value according to the maximum allowable velocity V_{\max} .

VIII. HYBRIDIZATION OF THE PSO AND GA

Novel approaches for applying to the PSO and GA methods simultaneously have been well researched and explored in computational studies [28]. Other hybrid approaches have also combined non-evolutionary methods with evolutionary ones, typically using gradients (or a numeric approximation of the gradient) combined with evolutionary methods [32]. The methodology applied herein was done as a two-step process, first taking a PSO update step, then producing offspring for each PSO point. The PSO was processed on the existing data points using the previous generations G_{best} and P_{best} locations, the genetic variants are taken by crossing over with random current generation PSO particles and exchanging selected fueling parameter information. The genetic variants are tested and the best performer is selected from each sub-population to represent the PSO particle. The resulting PSO position is then fed back to the PSO process so that a G_{best} and P_{best} can be identified from the selected population. The ratio of GA variants to test for each PSO particle was selected in order to maintain an equivalent ratio of GA and PSO searching with respect to evaluation time, rather than by the computational tradition of raw function evaluation counts.

Hybrid gradient methods may improve the GA more than they improve the PSO due to the nature of the PSO to naturally seek out improved solutions in a path-driven approach, while the GA methods do not specifically reward individuals for improvement in objective value beyond the selection criteria. Other applied hybrid methods which have utilized regression techniques along with evolutionary methods and have been quite successful but typically require a large amount of data to be analyzed [35]. Unfortunately, most current studies have neglected to compare the PSO-GA hybrid methods to basic PSO methods in order to determine if exploiting the advantages of hybrid methods can be realized on an experimental engine testing apparatus, especially one

with a variable cost function in evaluation time. As indicated by prior research, it is expected that controllable design parameters can be optimized separately from hardware design parameters and while most recently research has focused on modeling and computational realms while optimization of control parameters in actual engine test platforms has been somewhat neglected. By investigating and applying hybrid concepts adapted from the computational realm, experimental methods will be sought to improve controllable parameter optimization on the experimental engine apparatus. PSO and GA hybrids are often applied in novel ways using problem specific knowledge [21]. As identified by prior studies the PSO method advantage is primarily rapid convergence, especially in locally smooth regions. The GA advantages are primarily exploration and diversity, especially in convoluted and disjoint regions of feasible design space, and with highly complex response surfaces. Identifying which parameters are well suited to optimization by PSO and which are best suited to the GA requires engineering intuition, general problem-specific background knowledge, apparatus-specific knowledge, preliminary studies, or a substantial quantity of a priori decisions derived from prior explorations or research. This study constructed a PSO-GA stepwise hybrid using a PSO “step” followed by a GA “generation” in order to exploit a settling time difference in the test apparatus. No function evaluation took place between the two different steps so the current objective value of the “parent” particle is unknown when compared to the current generation. In this evaluation, however, the parent particle location is tested to demonstrate the type of improvements expected.

IX. CONTROL STRATEGY

There are different methods to monitor and manage the hybrid energy systems with non-intermittent resources such as wind and sun having their own advantages and disadvantages. The procedure of the proposed method is as follows:

If the total power generated by the solar arrays and wind units is equal to the load, the battery capacity remains unchanged. If the total power generated by the solar arrays and wind units is more than the load, the excess power generated by the hybrid system can be used to charge the battery bank. If the total power generated by the solar arrays and wind units are less than the load, the power deficit must be supplied by the battery and electrolysis to meet the load demand and the battery is discharged.

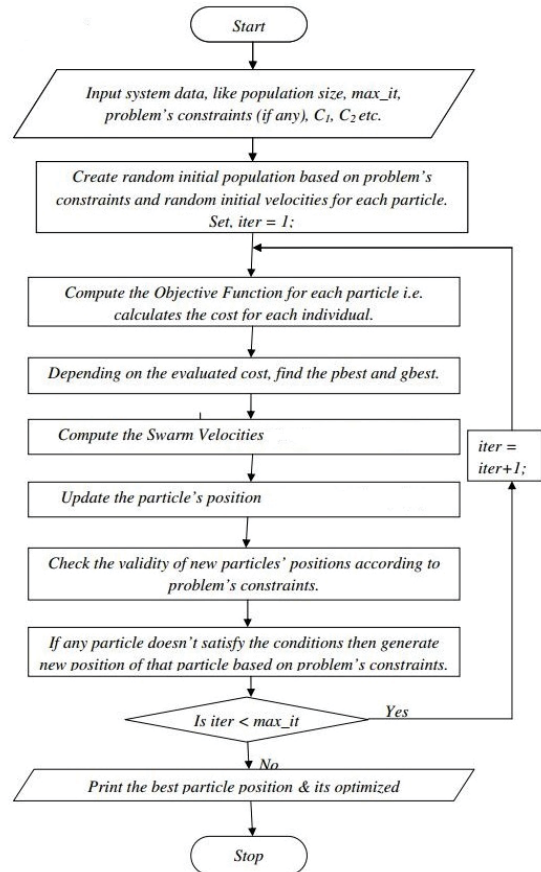


Fig. 14 Basic PSO Flowchart

X. SIMULATION RESULTS

To assess the capability of proposed method, the hybrid system has been modeled in terms of data pertaining to wind velocity, solar radiation and power in Kazerun. Average daily wind blow, solar radiation and power demand per year are shown in Figs. 15, 16 and 17, respectively. Also, daily solar radiation and wind velocity curves are shown in Figs. 18 and 19, respectively.

In order to assess the capability of proposed method by evolutionary algorithms, hybrid energy system is optimized considering renewable and non-renewable energy resources. It does incur investment and power plant utilization costs. All existing prices are real and equipment is available in the commercial marketplace. Table IV represents optimal solutions of PSO-GA algorithms with renewable power supply resources. Figs. 20 and 21 show optimal solutions, iterative frequency, optimized parameters, and total power production cost of hybrid energy system. Fig. 22 shows share of cost for optimized hybrid energy system components with high reliability.

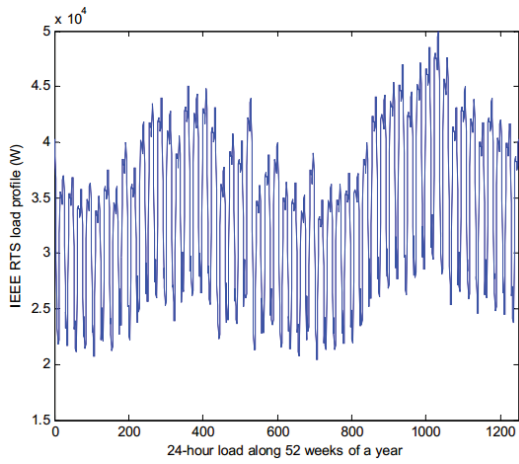


Fig. 15 Average daily power demand per year

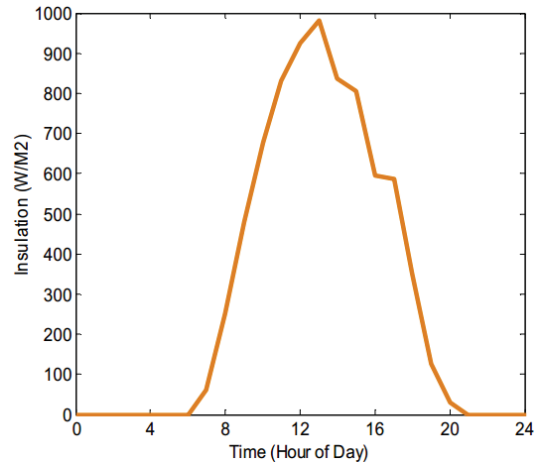


Fig. 18 The intensity of solar radiation per day

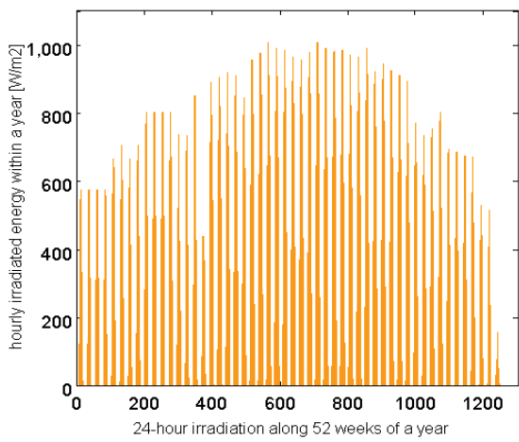


Fig. 16 Annual solar radiation

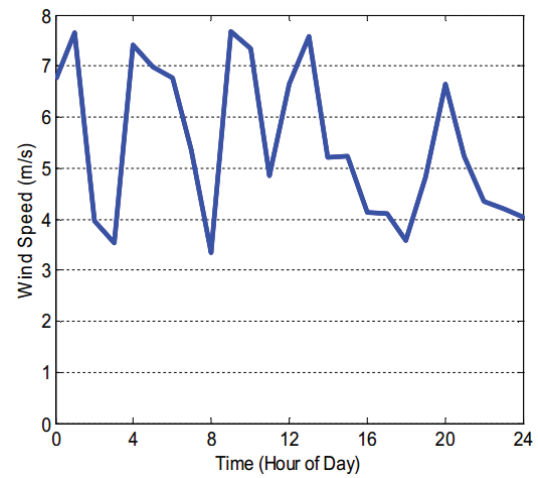


Fig. 19 Daily wind velocity

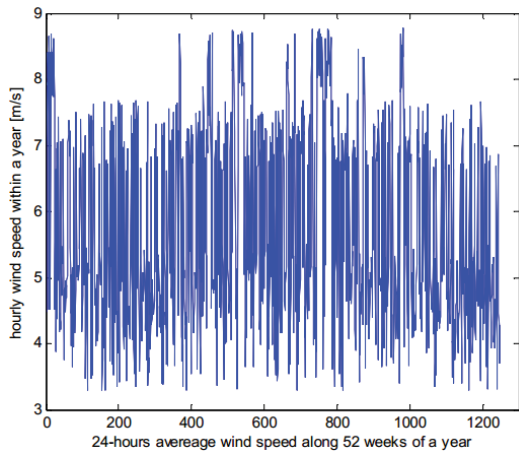


Fig. 17 Annual wind velocity

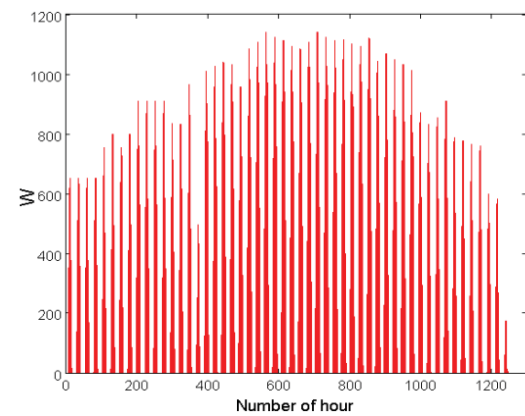


Fig. 20 Output power per PV panel unit

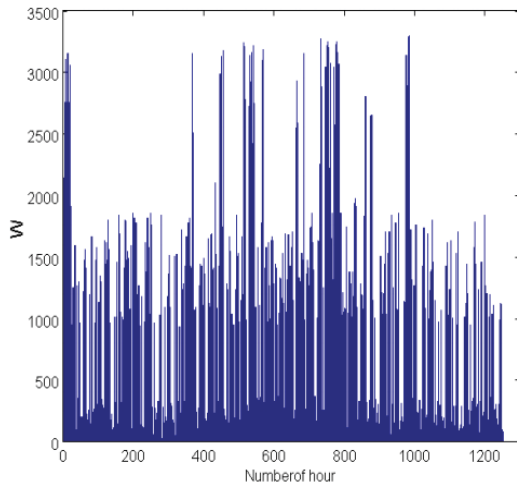


Fig. 21 Output power per wind turbine

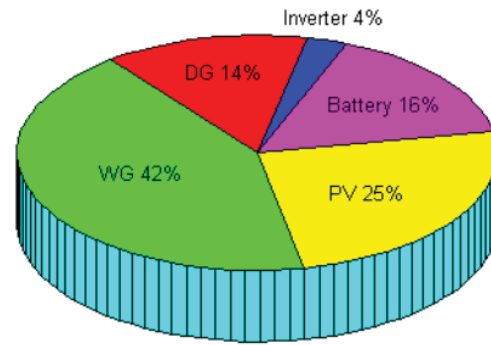


Fig. 22 Share of costs for system components

TABLE IV
OPTIMAL SOLUTIONS OF PSO-GA ALGORITHM FOR HYBRID ENERGY SYSTEM

optimal solutions	The number of repetitions	Optimized	Optimized	Optimized	Optimized	Optimized	total cost of 20 years (\$)	LPSP (%)
		N_{WG}	N_{PV}	N_{BAT}	DG_1	DG_2		
1	100	95	5	345	6	5	2606528	0.47
2	100	51	111	340	2	5	2531467	0.64
3	100	46	413	371	4	3	2489318	0.89

XI. CONCLUSION

Energy systems are often designed and utilized based on technical and economic considerations and reliability constraints. Choosing appropriate dimensions for hybrid systems can show a good ratio between cost and operation. Therefore, it is of great importance. Before determining system dimensions, the amount of power consumption and the intensity of radiation available need to be calculated. Here, evolutionary algorithms GA and PSO are used to optimize the dimensions of hybrid system and examine its performance. The study aims to minimize power plant cost during the system operation considering various constraints such as full coverage of power demand.

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