# Generation and Demand Scheduling in a Micro-grid with Battery-based Storage Systems, Hybrid Renewable Systems and Electric Vehicle Aggregators

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*Abstract:* This study presents a proposal for generation scheduling and demand response (electric vehicles in this study) of an isolated micro-grid. The system has the following elements: battery-based storage systems, hybrid renewable systems (wind and solar generators with controllable dispatch), traditional generators and electric vehicle aggregators for demand management. In order to reach economic and reliable operation of the system, a multi-objective optimization model considering battery life extension, in a side; and energy generation costs, and recharge price for electric vehicles, on the other side, is established. To address the variability and inherent stochastic nature of renewables, uncertainty cost functions for the hybrid renewable systems are used through probability density functions of the available resources. Additionally, in order to allow balancing the uncertainty and variability of renewable generation, Demand side management (DSM) is introduced into the optimization problem through controllable resources in the grid like plug-in electric vehicles (PEVs). A coordinated charging strategy is developed for PEVs through aggregators to obtain the most economic power dispatch scheme and the lowest charging price. The optimal set of operation parameters of the micro-grid is obtained using the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). Results show that the proposed methodology is useful to obtain a market environment able to handle the scheduling of generation resources and operation parameters of the micro-grid system.

*Key–Words:* Economic dispatch models, Mathematical modeling, Genetic Algorithms, Solar energy, Uncertainty cost.

## 1 Introduction

### 1.1 Motivation and incitement

In recent years, the increasing demand for energy and the penetration of renewable energy resources in the conventional power system has contributed to the emergence of a new power distribution scheme known as micro-grid. In this scheme, power generation is performed through de-centralized energy resources that are generally located near the load, most of this resources are based on renewable energy sources like wind and solar systems.

Micro-grids are most widely employed in areas where the main utility is not available due to several reasons. Generally, these areas are supplied by systems using a combination of diesel generators, renewable energy resources, and energy storage [1]. Plug-In Electric Vehicles (PEVs) have also been gradually started to be considered as a part of the micro-grid system [2]. The ever increasing concern for climate change and the high costs of fuel and transportation have promoted the employment of alternative energy as the main source of power generation; however, renewable resources are inherently stochastic and intermittent. To effectively take advantage of renewable energies, it is essential to develop operation strategies of the micro-grid system in which an optimal combination of energy resources meets the energy demand economically and reliably over a planning horizon.

In this way, micro-grids operators have the need of scheduling tools of elements like battery-based storage systems, hybrid renewable systems (wind and solar generators with controllable dispatch), traditional generators and electric vehicle aggregators for demand management. Demand response can be achieved by actively aggregating the energy demand of controllable loads such as PEVs, also, PEVs can be used advantageously as loads or as sources of energy to actively respond to the energy demand during a planning horizon. Thus, a market environment will be possible able to handle the scheduling of generation resources and operation parameters of the micro-grid system.

## 1.2 Literature review

Many authors have researched into the optimal operation of micro-grids problem. Nejad et al. [1] proposed a particle swarm optimization (PSO) technique to optimize the operation of a micro-grid involving wind turbines, micro turbines, and energy storage systems. In this research work, Monte Carlo simulation methods were applied to model the uncertainties of renewables; a probability distribution function was developed for all the decision variables. Siano et al. [2] proposed a multi-objective stochastic problem for the optimal operation of a micro-grid with thermal loads; the generation resources were a combination of conventional and non-conventional generation units including a combined heat and power plant (CHP) energy storage systems (both thermal and electrical) and renewables (Solar Photovoltaic and Wind). The proposed optimization methodology was based on a stochastic approach for modelling renewables uncertainties; the problem was solved using the augmented Epsilon-Constraint technique. The results obtained were compared against a genetic algorithm proving satisfactory performance.

Reddy et al. [3] researched into the optimal scheduling problem of a micro-grid consisting of conventional generators, solar photovoltaic systems, wind turbines, energy storage systems, and electric vehicles. The optimization problem was solved by using the hybrid differential evolution and harmony search (hybrid DE-HS) algorithm, simulation results demonstrated that the optimum cost of energy may be achieved by actively employing electric vehicles as energy sourcing elements. In [4] uncertainty of non-conventional energy was presented. In this research work a stochastic method was applied to solve the optimal operation problem of a micro-grid with uncertainties. Arevalo et al. [5] presented a research work in which uncertainty costs were assigned to the power delivered to the grid by renewable energy resources. The main contribution of this work was that, by including uncertainty costs in the intermittent resources, the cost function of the traditional scheduling problem was modified; in this way, the network operators have a decision tool based on probability distribution functions of resource availability to include the energy generated by renewable sources in their dispatch.

A probabilistic unit commitment (UC) model was developed in [6]; the considered micro-grid comprised wind turbines, micro turbines, electric vehicles, battery, and thermal storage units. A particle swarm optimization algorithm was employed to maximize the total expected profit of the UC schedule. The results reveal good performance of the proposed methodology. Abedini et al. [7] presented a guaranteed convergence Gaussian-Mutation Particle Swarm Optimization (GM-PSO) technique to solve the optimal management strategy problem for an autonomous micro-grid with wind turbines solar photovoltaic systems, and diesel generators. The results demonstrated that the hybrid battery-diesel design of systems with renewable energy sources is more efficient than the exclusive use of batteries or diesel generators.

Lifetime optimization of battery energy storage systems was researched by Das et al. [8]. In [9] an economic operation model of isolated micro-girds with micro gas turbines, wind turbines, heat pump, and battery-based energy storage system was presented. Fuel cell and battery integration alongside wind turbines and solar photovoltaic generators were studied in [10]. An optimal scheduling strategy was presented in [11] considering islanding operation constraints.

Moga et al. [12] researched into an optimization model based on the day-ahead forecasted power of non-controllable load. Additionally, a weather forecast was included to determine the solar energy available. The main purpose of the optimization model was to optimize the operation of three non-conventional sources (biogas, solar photovoltaic, and geothermal). An experimental test equipment with smart metering instruments was introduced to validate the model. Optimal day-ahead scheduling was presented by Zhang et al. [13] for a micro-grid system with wind turbines. The environmental economic dispatch of a micro-grid was solved by using cuckoo search algorithm (CSA) in [14], the results obtained from this method are compared with those obtained using a particle swarm optimizer; this method, yield better results. Trifkovic et al. [15] presented a parametric programming approach for the management of energy in micro-grids. In [16] an optimal operation planning for and isolated micro-grid with photovoltaic generators, wind turbines diesel generators, and batteries was presented. Stochastic economic load dispatch (SELD) for micro-grids was researched in [17]. The work presented in [18] employed a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to solve the optimal power allocation for storage batteries and diesel generators by means of the overall deliberation of the environmental and economic benefits of the system operation.

Rabiee et al. [19] presented a methodology in which the operation costs and emission of a micro-grid was minimized by optimal scheduling of electric vehicles and receptive loads. The results obtained proved that by means of integrating electric vehicles and reactive loads in the micro-grid an economic and environmental friendly operation of the micro-grid can be achieved. The table 1 shows the considerations of the previous work for operation scheduling in microgrids.

Table 1: Considerations of Scheduling Approaches

| Considerations | References |
|---|---|
| Demand Response | [1], [4], [5], [19] |
| Dynamic Voltage | [2] |
| Heuristic Optimization | [3], [7], [10], [13], [14], [15] |
| Stochastic optimization | [2], [4], [5], [17] |
| Robust optimization | [2], [8] |
| Energy Storage Systems | [5], [6], [8], [18] |
| Temperature Control Devices | [9] |
| Islanding capability | [10], [11], [16] |

### 1.3 Contribution and paper organization

The proposal of this work builds upon previously published research [1]-[19]; however, the main contribution of this research work is a methodology to successfully handle the inherent variability of energy generation through renewables by means of probability density and uncertainty costs functions while simultaneously extending battery lifetime and integrating controllable loads (such as PEVs) to the system. This makes it possible to a small extent, to achieve demand-side management. On the other hand, PEVs aggregation was not previously considered in the published research [1]-[19].

In this paper the NSGA-II algorithm is employed to find the optimal operation parameters of an isolated micro-grid. It is used as test bed a real micro-grid in the Dong-fushan island in China. The considered micro-grid consists of wind turbines, solar photovoltaic panels, diesel generators, battery, and a small population of PEVs. The multi-objective optimization problem focuses mainly on reducing the energy generation costs of the system including the costs of the energy required to recharge the PEVs. The second optimization objective is to extend the battery lifetime; this of course also has economic implications.

This paper is organized as follows. Section II presents the multi-objective optimization problem formulation and introduces the probability density functions to address renewables stochasticity; this section also presents a brief overview of the coordinated charge strategy of the PEVs. Section III describes the background of the test bed micro-grid system and its main components; additionally, presents a concise description of the NSGA-II genetic algorithm employed to solve the optimization problem. Section IV presents the obtained results and a discussion. Section V presents the conclusions.

## 2 Problem Formulation

Given the multi-objective nature of the problem, two optimization objectives can be identified:

- The cost minimization of energy generation using conventional and controllable renewable generators as well as the minimization of the energy costs to recharge Plug-In electric vehicles through demand response.
- The minimization of battery life loss. This objective is also economic, as the battery life extension represents a reduction in the cost of investment to replace the battery given its premature exhaustion.

Achieving the optimal scheduling of the micro-grid energy resources to meet the energy demand in real time is a must. However, the previous optimization objectives are to be reached while operating under the system constraints.

### 2.1 Cost of Generation with Conventional Generators

Traditionally, the cost function of a conventional generator can be modelled with a second-order polynomic cost function [20]-[21] that is closely related to the fuel cost function:

$$C_i(P_{gi}) = a_i {P_{gi}}^2 + b_i P_{gi} + c_i \tag{1}$$

Where: $a_i$, $b_i$ and $c$ are coefficients associated to the characteristics of each generator and $e_i$ and $f_i$ are fuel costs coefficients for the $i-th$ generator. Given this, the total generation cost for a system with $N$ conventional units is:

$$C_{conv} = \sum_{i=1}^{N} (a_i P_g i^2 + b_i P_{gi} + c_i) \quad (2)$$

In this way, a cost function for conventional generators is introduced analytically. Given that this cost function is a polynomial function, the optimization of the programming of conventional generation units in the dispatch of energy can be performed through conventional methods such as the Newton method [22], the gradient method [23], the gradient projection algorithm [24], quadratic programming [25]-[27], the decomposition technique [28], and approximations by MacLaurin series [29]-[30].

## 2.2 Cost of Generation with Hybrid Renewables

In this study a hybrid renewable is a wind or solar system able to be dispatchable. In order to reach this controllability, it is considered that the system has a back-up unit (normally a energy storage system) able to inject power in case of lack of resources or to charge in case of abundancy [31]-[33]. For including this behaviour in the problem target function, we propose to use uncertainty cost functions for solar and wind systems [5], [20].

### 2.2.1 Uncertainty Costs

Given the uncertainty of the power generated using renewable energies, the model that includes these resources in the energy dispatch must include a term to consider such uncertainty. Penalty costs are an addition to operative costs of energy generation. In a power system for a generation unit the scheduled power $W_{s,i}$ and the available $W_{av,i}$ power are under or over-estimated such that [5], [20]:

$$W_{s,i} < W_{av,i} \quad (3)$$

Or

$$W_{s,i} > W_{av,i} \quad (4)$$

For each case, a cost function is defined due to the under or over-estimation of the available power in the resource.

The cost for overestimating the available power in a renewable resource is defined by:

$$C_{o,i}(W_{s,i}, W_{av,i}) = c_{o,i}(W_{s,i} - W_{av,i}) \quad (5)$$

$c_{o,i}$ is a penalization coefficient defined by the system operator and corresponds to the costs of using the difference between the dispatch and scheduled power.

Similarly, the underestimation costs are defined as:

$$C_{u,i}(W_{s,i}, W_{av,i}) = c_{u,i}(W_{av,i} - W_{s,i}) \quad (6)$$

Uncertainty costs are defined as the expected value of the penalty functions for under or overestimating the available generation power. The uncertainty costs function (UCF) are obtained by adding the costs due to over and underestimation of the available resource.

$$UCF = C_{u,i}(W_{s,i}, W_{av,i}) + C_{o,i}(W_{s,i}, W_{av,i}) \quad (7)$$

The expected value of the penalty cost for underestimating is given by:

$$E[C_{u,i}(W_{s,i}, W_{av,i})] = \int_{W_{s,i}}^{W_{max,i}} c_{u,i}(W_{av,i} - W_{s,i}) \times f_W(W_{av,i}) dW_{av,i} \quad (8)$$

$f_W(W_{av,i})$ is the probability of certain power to be available on the energy source.
$W_{max,i}$ is the maximum power of the $i-th$ generator.

Similarly for the overestimated case:

$$E[C_{o,i}(W_{s,i}, W_{av,i})] = \int_{W_{min,i}}^{W_{s,i}} c_{o,i}(W_{s,i} - W_{av,i}) \times f_W(W_{av,i}) dW_{av,i} \quad (9)$$

$W_{min,i}$ is the minimum power output of the $i-th$ generator.

Given the inherent stochastic nature of the energy generated by renewable resources, a probability density function is used to determine the availability of the resource.

### 2.2.2 Solar Photovoltaic

Solar photovoltaic energy is generated by solar irradiance, which depends heavily on the geographical location. The following log-normal probability distribution function is used to obtain the expected value of the UCF [5], [20]:

$$f_g(G) = \frac{1}{G\beta\sqrt{2\pi}} e^{\frac{-ln(G)-\lambda^2}{2\beta^2}}, 0 < G < \infty \quad (10)$$

Where:

- $f_g(G)$ is the log-normal probability function.

- $G$ is the solar irradiance.
- $\lambda$ is the mean of the log-normal distribution.
- $\beta$ is the standard deviation of the Log-normal distribution.

The relationship between solar irradiance and the power generated by the photovoltaic panel is given by:

$$W_{PV}(G) = \begin{cases} \frac{W_{PVr}G^2}{G_r R_c} & 0 < G < R_c \\ \frac{W_{PVr}G}{G_r} & G > R_c \end{cases} \quad (11)$$

Where:

- $W_PV(G)$ is the photovoltaic power generated as a function of the solar irradiance.
- $G$ is the solar irradiance.
- $G_r$ is the standard ambience irradiance.
- $R_c$ is the reference irradiance.
- $W_{PVr}$ is the nominal output power of the photovoltaic cell.

$f_{W_{PV}(W_{PV})}$ is a function to obtain the probability of a determined available power from solar irradiance. In order to obtain $f_{W_{PV}(W_{PV})}$ for both cases in equation 11, the probabilistic variable change theory is used.

- First Condition: $0 < G \leq R_c$

The notation $g(G)$ function is used to represent $W_{PV}$, which is the photovoltaic power generated in terms of $G$; this is:

$$W_{PV}(G) = g(G) = \frac{W_{PVr}G^2}{G_r R_c} \quad (12)$$

Taking the inverse of $g$:

$$g^{-1}(W_{PV}) = \pm\sqrt{\frac{W_{PV}G_r R_c}{W_{PVr}}} \quad (13)$$

And its derivative:

$$\frac{dg^{-1}(W_{PV})}{dW_{PV}} = \sqrt{\frac{G_r R_c}{W_{PVr}}}\frac{1}{2\sqrt{W_{PV}}} \quad (14)$$

Now, applying the variable change, the equation for solar photovoltaic power is obtained:

$$f_{W_{PV}}(W_{PV}) = f_G(g^{-1}(W_{PV}))\left|\frac{dg^{-1}(W_{PV})}{dW_{PV}}\right| \quad (15)$$

Replacing equations (13) and (14) in (15) the following is obtained:

$$f_{W_{PV}}(W_{PV}) = \sqrt{\frac{G_r R_c}{W_{PVr}WPV}}\frac{1}{2}\left[\frac{1}{(\sqrt{W_{PV}G_r R_c})\beta\sqrt{2\pi}}e^{\frac{-ln(G)-\lambda^2}{2\beta^2}}\right] \quad (16)$$

In this case, $G = \frac{W_{PV}G_r R_c}{W_{PVr}}$. This expression is valid for the following power limits: $0 < W_{PV} < \frac{W_{PVr}R_c}{G_r}$.

- Second Condition: $G > R_c$

In this case:

$$W_{PV}(G) = g(G) = \frac{W_{PVr}G}{G_r} \quad (17)$$

The inverse of $g$ is determined by:

$$g^{-1}(W_{PV}) = \frac{W_{PV}G_r}{W_{PVr}} \quad (18)$$

Similarly, the derivative of $g^{-1}$ is determined by:

$$\frac{dg^{-1}(W_{PV})}{dW_{PV}} = \frac{G_r}{W_{PVr}} \quad (19)$$

Replacing equations (19) and (20) into (14):

$$f_{W_{PV}}(W_{PV}) = \frac{1}{\left(\frac{W_{PV}G_r}{W_{PVr}}\right)\beta\sqrt{2\pi}}e^{\frac{-ln(G)-\lambda^2}{2\beta^2}}\frac{G_r}{W_{PVr}} \quad (20)$$

The expression in (20) is valid for $W_{PV} \geq \frac{W_{PVr}R_c}{G_r}$. It is now possible to obtain the penalty costs due to underestimate or overestimate the power of the photovoltaic generator replacing equations (16) and (20) into equations (8) and (9).

#### 2.2.2.1 Penalty cost due to underestimate for Photovoltaic Generators

The uncertainty cost function related to the penalty cost given the underestimate case may be obtained by developing the following integral:

$$E[C_{PV,u,i}(W_{PV,s,i}, W_{PV,i})] = \int_{W_{PV,s,i}}^{W_{PV,\infty,i}} c_{PV,u,i}(W_{PV,i} - W_{PV,s,i}) \cdot f_{W_{PV}}(W_{PV,i}) \cdot dW_{PV,i} \quad (21)$$

Where:

- $E[C_{PV,u,i}(W_{PV,s,i}, W_{PV,i})]$ is the expected value of the underestimate penalty cost for the photovoltaic generator.

- $f_{W_{PV}}(W_{PV,i})$ is the probability distribution function of the power in the $i-th$ photovoltaic generator.
- $c_{PV,u,i}$ is the underestimate penalty cost coefficient for the $i-th$ photovoltaic generator.
- $W_{PV,\infty,i}$ is the maximum power output of the PV generator $i$.
- $W_{PV,s,i}$ is the scheduled power in the $i-th$ photovoltaic generator.
- $W_{PV,i}$ is the available power in the $i-th$ generator.

An output power $(W_{Rc})$, is associated directly with the irradiance value $R_c$. in equation (22).

$$\frac{W_{PVr}\cdot R_c}{G_r} = W_{Rc} \tag{22}$$

The integral in (21) is divided into two parts $A$ and $B$. After replacing and solving for each case, an expression for the expected value of the penalty costs functions can be obtained.

- *Condition A:* for $0 < W_{PV,i} \leq W_{Rc}$

$$E[C_{PV,u,i}(W_{PV,s,i},W_{PV,i}),A] = \frac{(-1)c_{PV,u,i}W_{PV,s,i}}{2}$$
$$\left[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}) - erf(\frac{\left(\frac{1}{2}ln(\frac{W_{PV,s,i}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\right]$$
$$+\frac{c_{PV,u,i}W_{PVr}\cdot e^{2\lambda+2\beta^2}}{2G_rR_c}\left[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\sqrt{2}\beta)\right.$$
$$\left.-erf(\frac{\left(\frac{1}{2}ln(\frac{W_{PV,s,i}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\sqrt{2}\beta)\right] \tag{23}$$

- *Condition B:* for $W_{PV,i} \geq W_{Rc}$

$$E[C_{PV,u,i}(W_{PV,s,i},W_{PV,i}),B] = \frac{c_{PV,u,i}W_{PV,s,i}}{2}\left[erf(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\right.$$
$$\left.-erf(\frac{\left(ln(\frac{W_{PV,\infty,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\right]$$
$$+\frac{c_{PV,u,i}W_{PVr}\cdot e^{\lambda+\beta^2/2}}{2\cdot G_r}\left[erf(\frac{\left(ln(\frac{W_{PV,\infty,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}})\right.$$
$$\left.-erf(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}})\right] \tag{24}$$

**2.2.2.2 Penalty cost due to overestimate for Photovoltaic Generators** The uncertainty cost function related to the penalty cost given the overestimate case can be obtained developing the following integral.

$$E[C_{PV,o,i}(W_{PV,s,i},W_{PV,i})] =$$
$$= \int_0^{W_{PV,s,i}} c_{PV,o,i}(W_{PV,s,i}-W_{PV,i})f_{W_{PV}}(W_{PV})\cdot dW_{PV,i} \tag{25}$$

Where:

- $E[C_{PV,o,i}(W_{PV,s,i},W_{PV,i})]$ is the expected value of the penalty cost due to overestimate for PVG case.
- $f_{W_{PV}}(W_{PV})$ is the PDF of the power of the photovoltaic generator $i$.
- $c_{PV,o,i}$ is the penalty cost coefficient due to overestimate in the PVG for generator $i$.
- $W_{PV,s,i}$ is the scheduled PV power set by ED model in generator $i$.
- $W_{PV,i}$ is the PV available power in the generator $i$.

Similarly to equation (21) integral (25) is divided into two parts:

- *Condition A:* for $0 < W_{PV,i} \leq W_{Rc}$

It is possible to obtain the expected penalty cost due to overestimate in the condition $A$ by replacing (20) in (25), after solving, the following expression for the expected penalty cost due to overestimate in condition $A$ is obtained:

$$E[C_{PV,o,i},(W_{PV,s,i},W_{PV,i}),A] = \frac{-c_{PV,o,i}W_{PV,s,i}}{2}\left[1\right.$$
$$\left.+erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta})\right]$$
$$+\frac{c_{PV,o,i}W_{PVr}\cdot e^{2\lambda+2\beta^2}}{G_rR_c2}\left[erf(\frac{\left(\frac{1}{2}ln(\frac{W_{Rc}G_rR_c}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\right.$$
$$\left.-\sqrt{2}\beta)+1\right] \tag{26}$$

- *Condition B:* for $W_{PV,i} > W_{Rc}$

Similarly the expected penalty cost due to overestimate in condition $B$ can be obtained replacing (12) in (25), after solving, the expression for the expected penalty cost due to overestimate in condition $B$ is obtained:

$$E[C_{PV,o,i},(W_{PV,s,i},W_{PV,i}),B] = \frac{c_{PV,o,i}W_{PV,s,i}}{2}\left[erf\left(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\right)\right.$$
$$\left. - erf\left(\frac{\left(ln(\frac{W_{PV,s,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}\right)\right]$$
$$+ \frac{c_{PV,o,i}W_{PVr}\cdot e^{\lambda+\beta^2/2}}{2\cdot G_r}\left[erf\left(\frac{\left(ln(\frac{W_{PV,s,i}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}}\right)\right.$$
$$\left. - erf\left(\frac{\left(ln(\frac{W_{Rc}G_r}{W_{PVr}})-\lambda\right)}{\sqrt{2}\beta}-\frac{\beta}{\sqrt{2}}\right)\right] \tag{27}$$

By adding equations (23), (24), (26) and (27) it is possible to get the Uncertainty cost functions for the photovoltaic generator.

Table 2: Parameters for photovoltaic generators

| **Parameter** | **Value** |
|---|---|
| $W_{pvr}$ | 20 (W) |
| $G_r$ | 1000 (W/$m^2$) |
| $R_c$ | 150 (W/$m^2$) |
| $W_{pv}$ | 100 (W) |

Some of the parameters for wind generators used in the problem formulation are summarized in table 2

### 2.2.3 Wind Power

Wind speed is the main parameter when generating energy through wind turbines, that for different geographic locations varies. The probability distribution for wind speed has been demonstrated to be either a Weibull or Rayleigh type whose parameters depend on the geographical location [5], [20].

$$f_v(v) = \frac{v}{\sigma^2}e^{\frac{-v^2}{2\sigma^2}} \tag{28}$$

Where:

- $f_v(v)$ is the probability density function for wind speed.
- $v$ is the wind speed.
- $\sigma$ is the geographical related scale factor.

The wind power generation is given by:

$$W_w(v) = \begin{cases} 0, & v < v_i; v > v_o \\ \rho v + \kappa, & v_i < v < v_r \\ W_r, & v_r < v < v_o \end{cases} \tag{29}$$

Where:

- $W_w(v)$ is the power generated as a function of wind speed.
- $v$ is the wind speed.
- $v_i$ is the lower cut speed of the aero-generator.
- $v_r$ is the nominal wind speed of the aero-generator.
- $v_o$ is the upper cut speed of the aero-generator.
- $W_r$ es the nominal output power o the aero-generator.

Also: $\rho = \frac{W_r}{v_r - v_i}$ and $\kappa = \frac{-W_r v_i}{v_r - v_i}$

- First Condition $v \leq v_i$ or $v \geq v_o$

In this condition the power generated due to insufficient wind speed or too much wind speed (leading to saturation) is 0. From this condition we get:

$$f_w(W_w = 0) = 1 - e^{-(\frac{v_i}{\sqrt{2}\sigma})^2} + e^{-(\frac{v_o}{\sqrt{2}\sigma})^2} \tag{30}$$

- Second Condition $v_i < v < v_r$

The relationship between the wind speed $v$ and the output power $W_w$ is given by:

$$W_w(v) = \rho v + \kappa \tag{31}$$

Based on the probability distribution function of wind expressed in equation (28) for values in the range of wind speed for condition B we can get:

$$f_W(0 < W_w < W_r) = \frac{W_w - \kappa}{\rho^2\sigma^2}e^{-(\frac{W_w - \kappa}{\sqrt{2}\rho\sigma})^2} \tag{32}$$

- Third Condition $v_r < v < v_o$

In this case, there is a constant power regardless of wind speed between $v_r$ and $v_o$. The probability distribution function for wind power can be obtained by:

$$f_W(W_w = W_r) = e^{-(\frac{v_r}{\sqrt{2}\sigma})^2} + e^{-(\frac{v_o}{\sqrt{2}\sigma})^2} \tag{33}$$

It is now possible to obtain the penalty costs due to underestimate or overestimate the power of the wind generator replacing equations (30), (32) and (33) into equations (8) and (9).

**2.2.3.1 Penalty cost due to underestimate for Wind Generators** The uncertainty cost function related to the penalty cost due to underestimate for wind generators can be obtained after solving the following integral:

$$E[C_{w,u,i}(W_{w,s,i}, W_{w,i})] = \int_{W_{w,s,i}}^{W_r} c_{w,u,i}(W_{w,i} - W_{w,s,i}) \cdot f_W(W_{w,i}) dW_{w,i} \tag{34}$$

Where:

- $E[C_{w,u,i}(W_{w,s,i}, W_{w,i})]$ is the expected value of the penalty cost due to underestimation for the wind generator case.
- $f_W(W_{w,i})$ is the probability density function of the power of the $i-th$ wind generator.
- $c_{w,u,i}$ is the penalty cost coefficient due to underestimation $i-th$ wind generator.
- $W_r$ is the maximum output power of the $i-th$ wind generator.
- $W_{w,s,i}$ is the scheduled power in the $i-th$ wind generator.
- $W_{w,i}$ is the available power in the $i-th$ wind generator.

After solving the integral, an expression for the expected penalty cost due to underestimation can be obtained:

$$\begin{aligned} E[C_{w,u,i}(W_{w,s,i}, W_{w,i})] = \frac{c_{w,u,i}}{2}\Big(\sqrt{2\pi}\rho\sigma(erf(\frac{W_{w,s,i}-\kappa}{\sqrt{2}\rho\sigma}) \\ - erf(\frac{W_r-\kappa}{\sqrt{2}\rho\sigma})) + 2(W_{w,s,i}-W_r)e^{-(\frac{W_r-\kappa}{\sqrt{2}\rho\sigma})^2}\Big) \\ + \frac{c_{w,u,i}}{2}(e^{-\frac{V_r^2}{2\sigma^2}} - e^{-\frac{V_0^2}{2\sigma^2}})(W_r - W_{w,s,i}) \end{aligned} \tag{35}$$

**2.2.3.2 Penalty cost due to overestimation for Wind Generators** The uncertainty cost function related to the penalty cost due to overestimate for wind generators can be obtained after solving the following integral:

$$E[C_{w,o,i}(W_{w,s,i}, W_{w,i})] = \int_{0}^{W_{w,s,i}} c_{w,o,i}(W_{w,s,i} - W_{w,i}) f_W(W_{w,i}) dW_{w,i} \tag{36}$$

Where:

- $E[C_{w,o,i}(W_{w,s,i}, W_{w,i})]$ is the expected value of the penalty cost due to overestimate for the wind generator case.
- $f_W(W_{w,i})$ is the probability density function of the power of the $i-th$ wind generator.
- $c_{w,o,i}$ is the penalty cost coefficient due to overestimate $i-th$ wind generator.
- $W_{w,s,i}$ is the scheduled power in the $i-th$ wind generator.
- $W_{w,i}$ is the available power in the $i-th$ wind generator.

After solving the integral, an expression for the expected penalty cost due to overestimate can be obtained:

$$\begin{aligned} E[C_{w,o,i}(W_{w,s,i}, W_{w,i})] = c_{w,o,i}W_{w,s,i} \cdot (1 - e^{-\frac{V_i^2}{2\sigma^2}} + e^{-\frac{V_0^2}{2\sigma^2}} \\ + e^{-\frac{\kappa^2}{2\rho^2\sigma^2}}) - \frac{\sqrt{2\pi}c_{w,o,i}\rho\sigma}{2}\Big(erf(\frac{W_{w,s,i}-\kappa}{\sqrt{2}\rho\sigma}) \\ - erf(\frac{-\kappa}{\sqrt{2}\rho\sigma})\Big) \end{aligned} \tag{37}$$

In this way, it is possible to obtain the UCF for wind generators by adding the equations (35) and (37).

Table 3: Parameters for wind Generators

| Parameter | Value |
|---|---|
| $W_r$ | 29.93 (W) |
| $v_r$ | 14.47 (m/s) |
| $v_i$ | 4 (m/s) |
| $v_o$ | 16.03 (m/s) |

Some of the parameters for wind generators used in the problem formulation are summarized in table 3

## 2.3 Plug-In Electric Vehicles

The cost function for Plug-In Electric Vehicles in this paper is product of the work presented in [33]. A distributed charging system is implemented by means of parking lots with $N_i$ charging ports. Each parking lot is operated by an ”aggregator.” At each charging port within the parking lot, the power can be controlled by this aggregator. The energy to charge the electric vehicles is purchased by the aggregator from the utility at time-of-use (TOU) rates. A coordinated charging strategy is developed for discrete time intervals $t_k = t_0 + k\Delta_t$, $k = 0, 1, ...,$ where $t_0$ is the time at which the charging strategy starts and $\Delta_t$ is the length of the time interval. Each electric vehicle can be charged with a power $p_{n_i}$ at port $n_i$; A variation from 0 to the rated power of the charging port $P_{max}$ is possible for each charging port in the parking lot. The initial State-Of-Charge (SOC) and arrival and departure behavior of the PEVs are uncertain; however they can be modelled using porbability distribution functions. When a PEV is connected to the system, the aggregator instantaneously obtains its battery capacity $B_{ni}$ and initial SOC ($SOC^A_{ni} \in [0,1]$), the customer informs the expected parking duration $T_{n_i}$ and the desired SOC upon departure $SOC^D_{ni}$. Using this information each aggregator builds a day-ahead forecast of local base loads. The coordinated charging strategy is implemented in three main steps:

### 2.3.1 Charging load boundaries

In this step the aggregated load boundaries are computed per each aggregator. This is achieved by describing each PEV charging need in terms of its energy and power boundaries. In any case these boundaries must not exceed the rated charging power at any given charging port. To ensure problem feasibility, the maximum possible SOC a departure $SOC^{D,a}_{n_i}$ is computed:

$$SOC^{D,a}_{n_i} = min\left(SOC^D_{n_i}, SOC^A_{n_i} + \frac{H_{n_i}\rho P_{max}\Delta_t}{B_{n_i}}\right) \tag{38}$$

$\forall n_i \in N_i, \forall i \in I$

Where:

- $I$ is the number of parking lots
- $N_i$ is the number of charging ports at parking lot $i \in I$
- $\rho$ is the charging efficiency
- $H_i$ is the planning horizon of the parking lot
- $SOC^{D,a}_{n_i}$ is the maximum SOC of the PEV at the time of depature from chargin port $n_i$
- $SOC^A_{n_i}$ is the initial SOC of the PEV at arrival at por $n_i$

The upper and lower energy limits for a single PEV at $[t_k, t_{k+H_i-1}]$ can be obtained by:

$$e^{max}_{n_i}(t_{k+j}) = e^{min}_{n_i}(t_{k+j}) = SOC^{D,a}_{n_i} B_{n_i}, \quad j = H_{n_i}, ..., H_i, \forall n_i \in N_i, \forall i \in I \tag{39}$$

Similarly:

$$e^{min}_{n_i}(t_{k+j}) = max\left(e^{min}_{n_i}(t_{k+j+1}) - \rho P_{max}\Delta_t, SOC^A_{n_i} B_{n_i}\right) \quad j = 0, ..., H_{n_i} - 1, \forall n_i \in N_i, \forall i \in I \tag{40}$$

Also:

$$e^{max}_{n_i}(t_k) = SOC^A_{n_i} B_{n_i}, \forall n_i \in N_i, \forall i \in I \tag{41}$$

Finally:

$$e^{max}_{n_i}(t_{k+j}) = min\left(e^{max}_{n_i}(t_{k+j+1}) - \rho P_{max}\Delta_t, SOC^{D,a}_{n_i} B_{n_i}\right) \tag{42}$$

Where:

- $e^{max}_{n_i}(t_{k+j})$ is the energy upper limit for a given PEV at port $n_i$
- $e^{min}_{n_i}(t_{k+j})$ is the energy lower limit for a given PEV at port $n_i$

It can be seen that equation (39) establishes the energy state limits for a PEV after its departure. Equation (40) specifies that the minimum energy state of a given PEV at time interval $(k+j)$ must be, at most $\rho P_{max}\Delta_t$ lower than its energy state at $(k + j + 1)$ but cannot be lower than the state of energy upon its arrival. The upper limit of the charging power for a single PEV at $[t_k, t_{k+H_i-1}]$ is determined by the rated power of the charging port, this is:

$$p^{max}_{n_i}(t_{k+j}) = P_{max}, j = 0, ..., H_{n_i}-1, \forall n_i \in N_i, \forall i \in I \tag{43}$$

$p^{max}_{n_i}(t_{k+j})$ is the upper power limit for a single PEV, it can be as large as the rated power for the $i - th$ charging port when a PEV is connected or zero otherwise. Now that power and energy limits for each PEV in the $i - th$ parking lot are obtained, the aggregated limits of the parking lot can be obtained:

$$E^{min}_i(t_{k+j}) = \sum_{n_i \in N_i} e^{min}_{n_i}(t_{k+j}), j = 0, ..., H_i, \forall i \in I \tag{44}$$

$$E^{max}_i(t_{k+j}) = \sum_{n_i \in N_i} e^{max}_{n_i}(t_{k+j}), j = 0, ..., H_i, \forall i \in I \tag{45}$$

$$P^{max}_i(t_{k+j}) = min\left(\sum_{n_i \in N_i} p^{max}_{n_i}(t_{k+j}), A_i\zeta_i(t_{k+j})\lambda\right) \quad j = 0, ..., H_i - 1, \forall i \in I \tag{46}$$

Where:

- $E^{min}_i(t_{k+j})$ is the minimum aggregated energy at port $n_i$.
- $E^{max}_i(t_{k+j})$ is the maximum aggregated energy at port $n_i$.

- $\zeta_i(t_{k+j})$ is the available capacity of the local distribution transformer that can be used fo supplying energy to the parking lot.
- $A_i$ is the capacity of the local distribution transformer.
- $\lambda$ is the charging power average power factor.

The aim of the charging strategy is to minimize the energy purchase costs and to achieve peak load controlling. Time-Of-Use (TOU) costs are summarized in table 4.

Table 4: Costs Per TOU

| Hour | \$/kWh |
|---|---|
| 8.00-12.00 | 0.138 |
| 12.00-17.00 | 0.109 |
| 0.00-8.00 | 0.058 |

A model for the coordinated charging strategy can be introduced as follows:

$$min_{\theta,p_i^{pref}} J(t_k) = \sum_{i\in I}\sum_{j=0}^{H-1} c(t_{k+j})p_i^{pref}(t_{k+j})\Delta_t + \mu\sum_{j=0}^{H-1}\theta(t) - \kappa\sum_{j=0}^{H-1}(H-j)p_i^{pref}(t_{k+j}) \quad (47)$$

Subject to:

$$p_i^{pref}(t_{k+j}) \leq P_i^{max}(t_{k+j}), j=0,\ldots,H_i-1, \forall i \in I$$
$$p_i^{pref}(t_{k+j}) = 0, j = H_i,\ldots,H, \forall i \in I$$
$$E_i^{min}(t_{k+j}) \leq \sum_{\tau=0}^{J-1} \rho p_i^{pref}(t_{t+\tau})\Delta_t + E_i^{max}(t_k) \leq E^{max(t_{k+J})}$$
$$J = 1,\ldots,H_i, \forall i \in I$$
$$\sum_{i\in I} p_i^{pref}(t_{k+j}) \leq A_T(t_{k+j}) - L_b(t_{k+j}) + \theta(t_{k+j}),$$
$$j = 0,\ldots,H-1 \quad (48)$$

Where:

- $A_T(t_{k+j})$ is the upper boundary of the load at the $(k+j)$ time interval.
- $L_b(t_{k+j})$ is the aggregated load of the primary transformer at the $(k+j)$ time interval.
- $H$ is the planning horizon.
- $c(t_{k+j})$ is the TOU price of energy for the aggregators at $(k+j)$ time interval.
- $p_i^{pref}(t_{k+j})$ is the preferred charging load for aggregator $i$ at time interval $(k<+j)$.
- $\theta(t_{k+j})$ is the slack variable used to achieve problem feasibility.
- $\mu$ is a penalty factor for positive slack variables $\theta$.
- $\kappa$ is a coefficient related to early charging preference.

In equation (47) the first term is used to minimize the cost at which each aggregator purchases electricity from the utility over the planning horizon, $\theta$ is a term introduced to penalize violation to the capacity limit and ensures problem feasibility, and the term $\kappa$ indicates preference for early charging.

The model presented above is related directly to the number of aggregators and to the planning horizon. However, it does not consider the number of PEVs connected. The optimization of the energy price for PEVs is for the price rate at which the aggregator buys energy from the utility so it can sell the energy to the users and make profit. From this point of view and for the scope of this work we will assume that the utility operator and the aggregator are the same, and that the optimized energy prices are directly transferred to the users, this assumption is valid in the view that the studied system is an isolated grid in a small area in which it makes sense that only one agent acts as energy generator and distributor.

## 2.4 Battery-Based Energy Storage

The cost function for Battery-Based Energy Storage in this paper is product of the work presented in [21]. Battery-based energy storage systems play a major role in the operation of isolated micro-grids. The strategy to dispatch the energy stored in the batteries can greatly impact their lifetime; this is of great importance if one considers the investment that needs to be made to install and operate such system [21]. At any given time during the micro-grid operation, the battery State-Of-Charge (SOC) must remain within a specified range with the purpose of aim battery lifetime:

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (49)$$

The charge or discharge power of the batteries must also remain between certain limits:

$$P_{chmax} \leq P_{batt} \leq P_{dischmax} \quad (50)$$

The value of the battery SOC during the time interval $t + \Delta t$ is determined by the instantaneous value of the SOC in the time $t$ plus the battery power during the time interval $\Delta t$:

$$SOC_{t+\delta t} = SOC_t - \frac{P_{bat-t}\Delta t}{C_{bat}} \tag{51}$$

$P_{bat-t}$ is the battery power between $t$ and $t + \Delta t$ and $C_{bat}$ is the battery capacity measured in Ah. Several studies have demonstrated that operating batteries at a high SOC may help extend its lifetime [31]-[33]. The objective is to keep the batteries operating at a high SOC.

#### 2.4.1 Costs of Lifetime Loss

The level of ageing of a battery can be measured by means of the battery capacity to store charge with respect to its capacity when it was new:

$$L_{loss} = \frac{Q_t}{Q_n} \tag{52}$$

Where $Q_t$ is the charge that the battery is able to store at instant $t$ and $Q_n$ is the nominal battery capacity when it was new. The costs function of the battery lifetime loss is related to the percentage of lifetime loss of the battery and the initial cost of investment in the battery-based energy storage system:

$$C_{batt} = L_{loss} C_{batt0} \tag{53}$$

Where $C_batt$ is the battery loss of lifetime cost and $C_batt0$ is the total initial investment cost to purchase the battery-based energy storage system. So, for a system with $N_{batt}$ battery-based energy storage systems, the aggregated cost function of battery loss of lifetime is given by:

$$C_{batt} = \sum_{n=1}^{N_{batt}} C_{batt_i} \tag{54}$$

Some of the battery parameters for the operation strategy are summarized in table 5

Table 5: Battery Operation Parameters

| Name | Parameter | Value |
|---|---|---|
| $SOC_{min}$ | Minimun SOC | 0.5 |
| $SOC_{max}$ | Maximum SOC | 0.95 |
| $SOC_i$ | Initial SOC | 0.6 |
| $Q$ | Ah of the Battery | 1000 Ah |

The associated costs for each resource in the micro-grid is summarized in table 6

Table 6: Energy price per resource per kWh

| Resource | Price (USD/kWh) |
|---|---|
| **Diesel** | 0.8 |
| **Batteries** | 180 |
| **Solar** | 0.0803 |
| **Wind** | 0.130 |

In this way, section 2.1, 2.2 and 2.3 correspond to the first optimization objective and section 2.4 corresponds to the second optimization objective.

## 3 Test Bed Background and Multi-Objective Solution Algorithm

### 3.1 Test Bed Micro-grid

The Dongji islands are a group of small islands located in the far east of China, in the Zhoushan archipelago [21]. The Dong-fushan island is the farthest inhabited island from the group. Up until recently, the main source for electricity generation in the island was based on polluting sources like diesel. Given the high costs and diffculty of transportation of the diesel fuel, the electricity supply was limited to short periods of availability. In September 2010, the Dong-fushan micro-grid system project started. The main objective of the project was to exploit the potential benefits from renewable resources in the island. The project was completed in April 2011 and has been operating since [21]. The proposed system included a water desalination plant, to address the water supply problem of the island, the main components of the system, quantity and its rated power are summarized in table 7:

Table 7: Hybrid Wind-Solar-Diesel-Battery System Components

| Type | PV | WT | Diesel | Lead-Acid Battery |
|---|---|---|---|---|
| **Power** | 180 W | 30 kW | 200 kW | 2 V /1000 Ah |
| **Quantity** | 556 | 7 | 1 | 480 |
| **Capacity** | 100 kW | 210 kW | 200 kW | 960 kWh |

The lead-acid battery array and photovoltaic array are connected to a common 750 V DC bus; from this point on, an inverter ties the 750 V DC bus to a 380 V AC bus. The power from the wind turbines are converted twice before beign delivered to the 380V AC bus to which the diesel converter is directly tied. An old diesel generator is also present in the system and is used as a backup in case the new system fails. The load, and seawater desalination plant are tied to the secondary of a 10 kV/380 V transformer, as shown in figure 1:

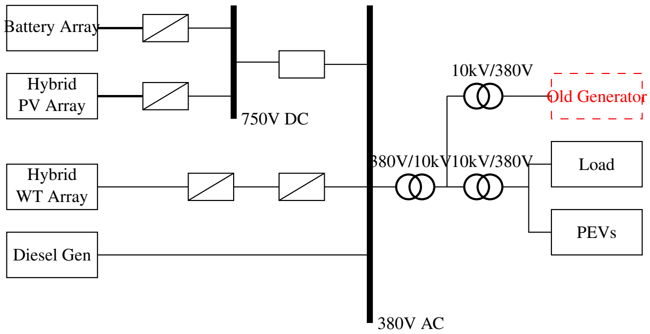


Figure 1: Schematic Diagram of the Hybrid Wind-Solar-Diesel-Battery System in the Dong-fushan Island

The system implemented in the Dong-fushan island operates using a master-slave strategy as presented in [21]. The battery array and the diesel generator serve as the master control unit alternatively depending on the operating conditions of the system. The operation strategy of the systems revolves around the battery array state-of-charge (SOC). Initially the battery array serves as the master unit. In this moment, the battery can be either charging, discharging, or in standby mode. This depends on the energy demand $P_{load}$ and the generated power by the renewable resources $P_{ren}$ and $P_{excess}$, which is the excess power generated from renewable resources that allow the battery to be charged. This mode of operation holds until the battery pack SOC falls below its $SOC_{min}$. When this happens the diesel generator becomes master unit and the battery starts to charge; a battery SOC threshold $SOC_{stp}$ is defined so that, when the battery SOC reaches this value, effectively stops the diesel generator and the batteries become the master unit again. When there is high availability of renewable resources (such as wind or solar radiation) the power generated from these resources is directly used to meet the energy demand in real time and to keep the power balance. In this moment, the battery can be either charging or in standby mode depending on the amount of energy generated. PEVs act as a load to the system, the goal of the optimization problem including electric vehicles is to achieve the lowest price for the required energy to recharge the battery of the vehicles. A time-of-use (TOU) approach is used in order to determine the price of the energy required to recharge the vehicle battery based on the time of the day of connection and the duration of the re-charge process.

## 3.2 The NSGA-II Genetic Algorithm

Genetic algorithms are a family of meta-heuristic and multi-objective optimizations algorithms inspired by the process of natural selection. Genetic algorithms largely rely on bio-inspired operators such as mutation, cross-over, and selection that act on a population of candidate solutions to an optimization problem.

Many engineering optimization problems are based on the process of minimizing a cost function that can be constrained or un-constrained. Such optimization problems are usually multi-objective, and as such, a single global optimal solution is not feasible, this is, the conflicting objectives may not be always fully achieved individually, instead, the best trade-off between this conflicting objectives is considered the best solution to an optimization problem.

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) was proposed in [33]. This algorithm starts with a population of individuals that are candidate solutions in a search space. The population is sorted into different levels of non-domination. Initially a population $P$ of size $N$ produces an offspring population $Q$ through genetic manipulation, that is, crossover and mutation. The resulting population and the original population are combined to produce population $R$. From this point onwards, the algorithm may be described by the following steps:

1. Population $R$ is classified according to the Pareto-rank mainly based on fitness criteria. Small intensity and small Pareto-rank principles are used to select individuals from this parent population and the new parent population $P'$ with size $N$ is created.

2. From $P'$ through genetic manipulation, generate population $Q'$.

3. A new population $R'$ is generated from $P'$ and $Q'$.

4. These steps are repeated until the stop criteria matches the specified condition.

The appropiate parameter combination for the genetic algorithm will surely result in a faster convergence to a solution. However, the general approach to determine this combination of parameters generally relies on trials of different combinations, for which repetitiveness of the obtained solutions must be assured.

Given the master-slave control strategy discussed in section 2 for the system, the control variables are defined to be $SOC_{stp}$ as the battery SOC threshold to change the master control unit in the system, also as a system constraint to keep the battery operating at a high SOC and extend its lifetime. $P_{excess}$ and $P_{charge}$ are variables of decision, the objective is to find their optimal values using the NSGA-II Algorithm. The optimization goals are defined to be the economic operation of the system and the extension of the battery lifetime. The value of $SOC_{min}$ is set at 0.6, $SOC_{max}$ is set at 0.95. The initial population size is set to be 200 and the generation number was set to be 20. The costs of the energy to recharge the electric vehicles is set based on the TOU costs. The following section, presents the results obtained.

## 4 Results and Discussion

In this work, charging efficiency and other practical factors are neglected. Figure 2 shows the renewable resources availability (i.e. Wind Speed and Solar Radiation). The power output from the wind turbines and solar photovoltaic panels can be obtained using equations (11) and (29). The optimal set of values $SOC_{stp}$, $P_{excess}$, and $P_{charge}$ are found through optimization process for three different operation scenarios.

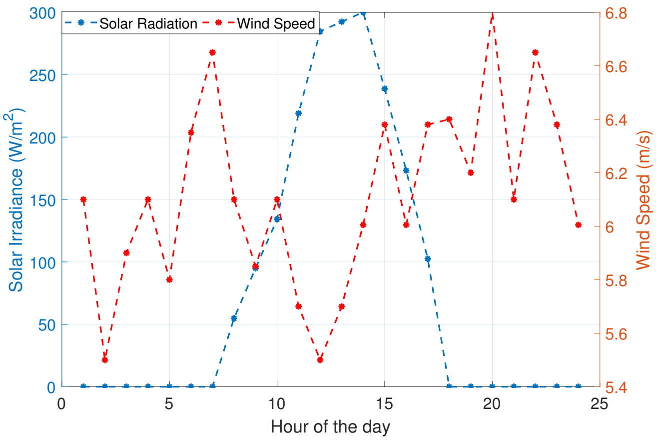


Figure 2: Solar radiation and wind speed availability throughout the day

Table 8: Optimized Values for Different Operating Scenarios

| **No.** | $SOC_{stp}$ | $P_{excess}$ | $P_{charge}$ |
|---|---|---|---|
| **1** | 0.8521 | 7.3473 | 61.3281 |
| **2** | 0.8613 | 34.6975 | 80.9329 |
| **3** | 0.9289 | 88.8963 | 84.5263 |

Table 8 summarizes the optimized values of $SOC_{stp}$, $P_{excess}$, and $P_{charge}$. The first operation scenario minimizes the cost of energy generation. However, battery life loss increases because $SOC_{stp}$ is set at a lower value meaning that the batteries are allowed to operate in a lower SOC.

In this way the time of operation of the diesel generator decreases and so does the energy price of the system. $P_{excess}$ is set at 7.3473kW; this means that the charging process of the batteries can be done partly with renewables and, that most of the power generated from renewable resources is used to meet the energy demand of the system.

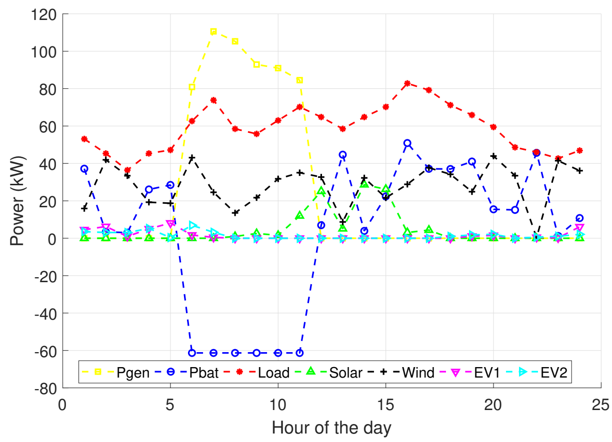


Figure 3: Resource scheduling for lowest energy price

According to 3, starting in the early hours of the planning horizon most of the energy demand is met by a combination of energy from wind turbines and batteries; this is also true for the aggregated energy demand of the PEVs aggregator, shown in 4. A combination of renewables and energy from batteries will surely result in a cost of energy lower than the cost from generating with the diesel generator. However, the energy generated from wind alone is not enough to meet the energy demand as it evolves along the planning horizon; this forces the battery to discharge to the $SOC_{stp}$ value, that is fixed at a lower value. The latter of course results in a greater loss of battery life and an increased cost of investment in replacing the battery given its premature exhaustion.

The energy demand rise forces the diesel generator to start operating as the aggregated power generation from renewables is not enough to meet the energy demand. In this case, most of the energy generated with the diesel generator is sent to the battery to recharge it, and the demand is met with a combination of diesel generation and renewables, This combination is the least favorable form the energy costs point of view, this is why in this operation scheme the PEVs do not charge.

Lastly, when solar power becomes available the combined wind-solar-battery energy generation scheme meets the energy demand. This is not the

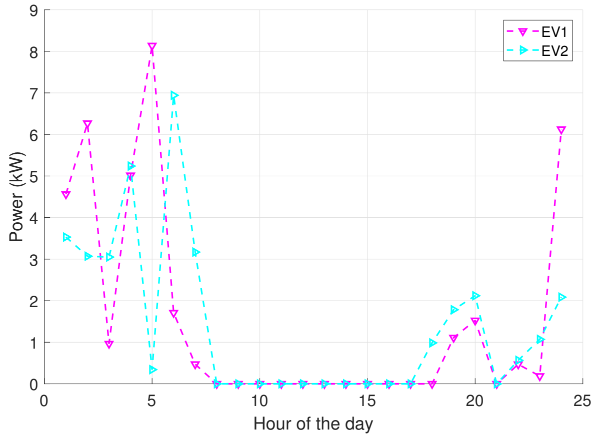


Figure 4: Coordinated charge strategy for the lowest energy price

optimal operation scenario as the battery is operating constantly and switching its operational state, thereby, contributing to its lifetime loss.

The operation scheme No. 2 shown in figures 5 and 6 (Coordinated PEVs Charge), $SOC_{stp}$ is set higher. This means that the diesel generator will have to generate more power before the batteries become master in the system. It also means that the energy price will increase in relation to the previous operating scenario given required additional diesel generation to charge the batteries to their new $SOC_{stp}$. However, an increased $SOC_{stp}$ will result in a reduction in life loss of the battery. $P_{excess}$ is set at 34.6975 kW this way, more power generated from renewable sources is used to charge the batteries but also to meet the energy demand of the system.

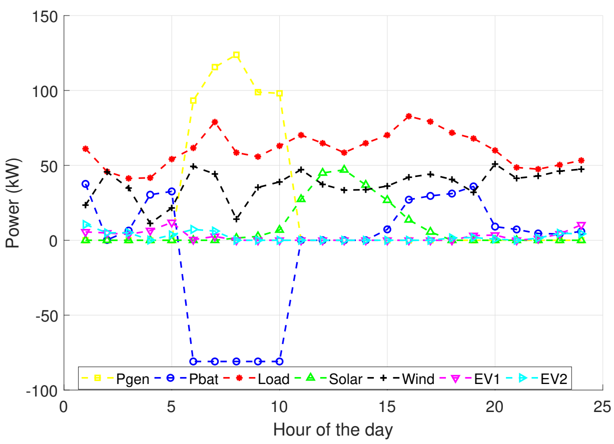


Figure 5: Resource scheduling for balanced energy price and battery lifetime loss reduction

The early hours of operation in the planning horizon are almost the same as in the previous operation scenario. However, the diesel generation is higher, resulting in slightly higher energy prices. As the system operates along the planning horizon solar power becomes available and help reduce the energy required from the battery, reducing the switching of the battery between states and helping extend its lifetime. In this operation scenario the charging strategy of PEVs demands most of the energy during the hours of lower demand. This helps decrease load peaks and also results in a reduced energy price for the system aggregator.

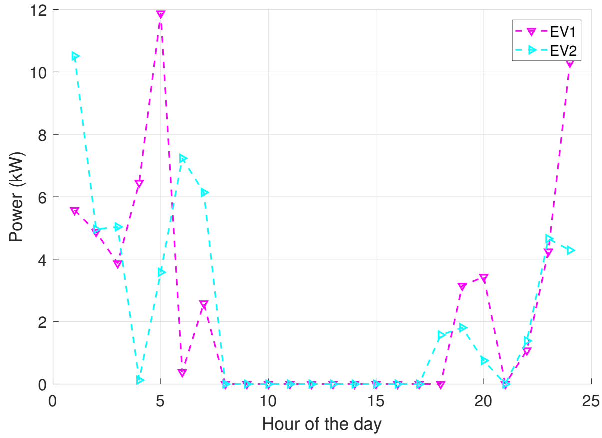


Figure 6: Coordinated charge strategy for balanced energy price and battery lifetime loss reduction

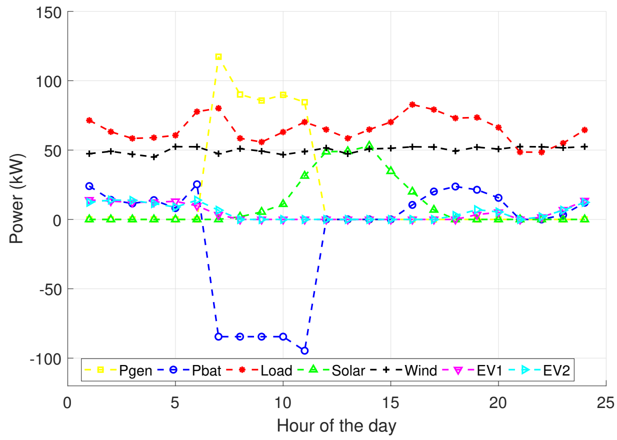


Figure 7: Resource scheduling for best battery life

In the last operation scenario the reduction in battery usage is evident (figures 7 and 8). Most of the energy demand is met with a combination of renewable resources and diesel generation. This, of course is a less favorable operation strategy considering energy price. However, it guarantees an extended lifetime of the battery. PEVs are charged in a way similar to that in the other operation strategies however as more power from renewables is available during more time, the PEVs demand is extendend. In this way a higher SOC for each PEV can be achieved at a low energy price for the system aggregator.

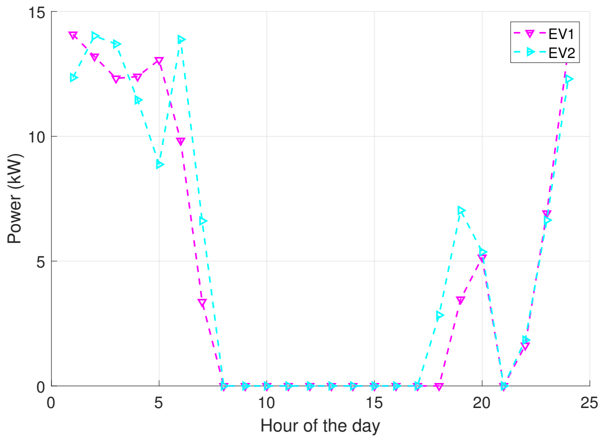


Figure 8: Coordinated charge strategy for best battery life

## 5 Conclusion

This study present a operation planning tool for micro-grids. In order to show the practical benefits of employing the propose tool, this paper presents the operation optimization of an isolated micro-grid in the Dong-fushan island in China. The major contribution of the work is the optimization of a set of parameters that rule the the micro-grid energy allocation during a planning horizon of 24 hours. A seamless integration of renewable energy sources is achieved by means of uncertainity costs functions. To meet the energy demand in the most economic way possible, both, from the energy price point of view and also from the battery lifetime extension point of view a combination of generation resources was devised using the Non-Dominated Sorting Genetic Algorithm - II (NSGA-II) for the planning horizon resulting in the lowest energy price and also the lowest loss of battery lifetime. Controllable loads like PEVs are used advantageously to respond to the energy demand throughout the planning horizon, this allows the energy demand to be modified by moving the aggregated demand of the PEVs to periods of generation were the energy price is lower. The main advantage of this approach, by employing the proposed strategy network, is that operators have a tool that allow them to integrate renewables in their energy dispatch and also to assign a price for the energy generated with such resources while simultaneously reducing the use of energy storage elements, and its consequent loss of lifetime.

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