A Case Study of Grid-Connected Solar Farm Control Using Artificial Intelligence Genetic Algorithm to Accommodate Peak Demand

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Abstract. The continuous rise in peak electricity demands is now considered to be one of the most prominent power generation problems. The need to increase generation capacity caused by peak demand growth is a critical economic issue due to the financial burdens associated with increasing capacity. Jordan is a good example of the problems caused by growing peak demand. As a small, aid-dependent country already suffering from financial and environmental issues, the number of Syrians seeking refuge in Jordan has created a strain on the country’s energy resources. This study examines the effect of installing a Photovoltaic (PV) solar farm at the Amman East Power Plant in order to offer a solution to the continuous growth in peak demand. As part of the research reported here, three mathematical representative models have been created and tested using real solar radiation, energy generation, and peak demand data. These results then were used to build a model based on an artificial intelligence Genetic Algorithm (GA) that could be used in predicting, analysing and calculating the best solar farm size in order to keep the generation curve as flat as possible with the least cost. Subsequently, an iterative simulation of the processes has been done to test the model different chromosomes: the optimum configuration of the model ensures that the annualized cost of the system (ACS) is minimized, while the peak demand is lessened as much as possible.

1. Introduction
Since the beginning of modern history, energy has considered as one of the most important human needs. This importance was supported by the continuous and steady technological development, cultural changes and industrial revolutions. The continuous growing energy demand attracted many scholars to develop the energy technologies, where energy production can be easier, cheaper and most importantly clean. The conventional energy generation methods which rely on the use of fossil fuel are producing different types of pollution; noise, air and environmental pollution are some examples. Besides, oil and its derivatives are exhaustible in the long run [1].
A promising source of energy is renewable energy. Renewable energy resources can provide clean cost-efficient and infinite energy. Those advantages accelerated the spread of renewable energy usage. Some raising renewable energy resources are solar energy, wind energy, biofuel energy, geothermal energy, tidal energy and biomass energy. Yet solar energy generation is of great interest for many reasons, the main reason is the huge potential amount of solar energy. Other factors that attracted the attention to solar energy in general and photovoltaic (PV) in particular are the ease and possibility of generating energy in various geographical regions [1]. However, the increasing reliance on renewable energy resources, especially solar energy, creates challenges that limit the ability to rely on these sources in a
holistic manner. These challenges come from the nature of solar energy (that depends on solar radiation) and its fluctuations during the year, season and even the day which causes production “uncertainty”. These challenges require reliable solutions such as developing storage methods and enhancing the solar radiation forecasting [2], especially for large scale applications, like grid-connected solar farms where any production fluctuations might affect the loss of power supply probability (LPSP). One of the major issues that can be solved by grid-connected solar farms is the peak demand growth [3]. There are many other methods for controlling peak demand and flattened its curve like Pricing strategies [4], nevertheless, pricing strategies are not fully efficient. Reise and White specify that a significant percentage of households do not respond to pricing strategies [5]. On the other hand, emerging technologies like Vehicle-to-Grid (V2G) strategies [6], scheduling and contorting energy consumption via smart grids [7] and Demand Side Management (DMS) in Smart Grid [8] might help in reducing or smoothing peak demand from the end users (customers) side. Alternatively, Solar power production is stochastic, where the generation peak is much higher than the average generation ratio. However, this flaw might be a key factor in solving peak demand growth if the peak generation and peak demand have matched in the time series. Larger solar farms designs are not the perfect solution to overcome peak demand, taking into consideration achieving the best economic benefits. Many factors play a major role to overcome the above-mentioned problems. Solar radiation, PV peak power, loss of load probability (LLP), LPSP and levelized cost of energy (LCE) [9] are among those factors. Thus, a good optimization between those factors is needed, where the load demand is to be met while the total costs are minimized. In the selection and evaluation of multi-criteria for designing grid-connected solar farms, the advantages and disadvantages of each criterion should be considered. Hence multi-criteria methods are needed to solve such problems [10]. Many techniques are used for multi-criteria optimization such as iterative technique, graphical construction and the probabilistic approach [11]. In [11] and [12] the genetic algorithm (GA) was used for modelling an optimal design, the results show that GA is a robust method for finding optimal solutions especially in multi-criteria optimization problems. For that reason, Artificial intelligence (AI) genetic algorithm was used in this study.

2. Data
The data used in this study is an outcome of real conditions. The generation (load) data were collected every hour at Amman East Power Plant, Amman-Jordan between the 1st of January 2014 to the 26th of May 2015. Solar radiation and temperature were collected every ten minutes at the National Energy Research Centre, Amman-Jordan for the same period. Large variations on temperature were recorded in this period which confirms the variety and validity of the experimental data. The minimum temperature recorded during the data collection was (Celsius) -3.3, the highest was 35.9 while the average was 15.51. The highest solar radiation was 1144 \( \text{wm}^{-2} \), the average solar radiation was 222 \( 4\text{wm}^{-2} \). The highest generation peak demand was 3111.399 \( Mw \), while the average demand was 2052.018 \( Mw \).

3. Discussion
Since solar energy generation depends on solar radiation, it is very useful to create a mathematical representative model for solar radiation. A representative model for solar radiation and generation data was created. Those two models are used in this study by AI GA for the optimization solution.

3.1. Solar radiation and potential energy generation modeling
Matlab’s curve fitting tool was used to create the mathematical representative models for both solar radiation and generation load. Figure 1 shows the mathematical representative model for solar radiation. Sum of sine with two terms (equation (1)) is the finest representative model, with R-square of 0.9968.

\[
f(x) = a1 \cdot \sin(b1 \cdot x + c1) + a2 \cdot \sin(b2 \cdot x + c2)
\]  

(1)

Coefficients: \( a1= 0.5212, b1= 1.195, c1= 1.429, \quad a2= 0.225, b2=3.583, c2=1.141 \). It can be observed from the model that the highest average solar radiation occurs at noon time, around 12:00 clock.
there is no significant radiation received before 6:00 or after 19:00. This model is useful for estimating the average annual energy generation by applying the following equation:

\[ P_m = \eta \cdot E \cdot A \]  

(2)

The energy conversion efficiency \( \eta \) is affected by the ambient temperature of the solar cell [13], thus in order to calculate \( P_m \) accurately under different temperatures the overall cell temperature coefficient (\( \mu \)) should be counted in equation (2) as the following [14]:

\[ P_m = (\eta - \mu(Tc - Ts)) \cdot E \cdot A \]  

(3)

Where \( P_m \) is the maximum power output in Watts at the standard conditions, \( \eta \) is the energy conversion efficiency, \( E \) the input solar irradiance (\( \text{w} \cdot \text{m}^{-2} \)) and \( A \) is the surface area of the solar cell (\( \text{m}^2 \)). \( Tc \) and \( Ts \) are (in order) the solar cell and the standard test temperature. To calculate the potential power that can be generated in different conditions where the solar radiation is not necessary 1000 \( \text{w} \cdot \text{m}^{-2} \), for the same solar cell area, equation (2) can be modified to [1]:

\[ P_{potential} = P_m \cdot E_{measured} \cdot E^{-1} \]  

(4)

Where \( P_{potential} \) is the potential amount of energy in Watts that can be generated under certain solar radiation \( E_{measured} \). Substitute equations (3) and (4), \( P_{potential} \) can be calculated.

\[ P_{potential} = (\eta - \mu(Tc - Ts)) \cdot E_{measured} \cdot A \]  

(5)

The potential power that can be generated after the total system losses in cables, dust covering panels and other losses is expressed by equation (6):

\[ P_{potential} = (\eta - \mu(Tc - Ts)) \cdot E_{measured} \cdot A \cdot \eta_{loss} \]  

(6)

Where \( \eta_{loss} \) is the factor representing the total system losses. \( E_{measured} \) was represented by equation (1) so the equation (6) become:

\[ P_{potential} = (\eta - \mu(Tc - Ts)) \cdot a1 \cdot \sin(b1 \cdot x + c1) + a2 \cdot \sin(b2 \cdot x + c2) \cdot A \cdot \eta_{loss} \]  

(7)

3.2. Load demand modeling

To overcome peak demand, peak demand must be studied first; a descriptive mathematical model makes it easier for the analysis. Figure 2 shows the mathematical representative model of the generation data (load demand curve). Fourier 3 (Fourier with three terms) (equation (8)) is the finest representative model, with R-square of 0.9957.
\[ f(x) = a_0 + a_1 \cdot \cos(x \cdot w) + b_1 \cdot \sin(x \cdot w) + a_2 \cdot \cos(2 \cdot x \cdot w) + b_2 \cdot \sin(2 \cdot x \cdot w) + a_3 \cdot \cos(3 \cdot x \cdot w) + b_3 \cdot \sin(3 \cdot x \cdot w) \]  

(8)

Coefficients: \(a_0 = 1980, a_1 = -285.5, b_1 = 62.41, a_2 = 62.97, b_2 = -42.3, a_3 = 79.13, b_3 = -97.3, w = 0.1892\)

It can be noticed from the model below that the generation has two peak demand, the first peak starts at 11:00 and remains till 14:00 before it starts to decrease slightly. This decrease continues slowly till 16:00. After 16:00 the demand starts to grow up again to reach the second peak at 18:00.

![Figure 2. Generation load representative model](image)

It can be perceived that peak solar radiation and first peak demand occur at the same time. Using solar energy to overcome peak demand can be useful for the first peak demand, while during the second peak demand, solar radiation droppers rapidly, and it can’t be considered as a solution for the second peak demand.

3.3. Load demand modeling

An electrical power system must sufficiently feed power to the load demand during a certain period to be considered as reliable, that means the reliable electric power systems must have a small loss of power supply probability (LPSP) [11]. LPSP is defined as the probability that the electrical power system (solar PV system in this study) cannot deliver sufficient power to the load. Normally, sufficient power is the power needed by the load during a certain time, as this study testing peak demand, the sufficient power will be the amount of power needed to decrease the peak demand to a certain acceptable level with least costs. Consequently, the LPSP is optimized by GA to ensure the least LPSP with least ACS to achieve the best economic benefits. An LPSP of 0 means the generated power will be 100% sufficient; and an LPSP of 1 means that the generated power will be 0% sufficient. LPSP can be mathematically represented by equation (9):

\[ LPSP = \sum (P_{load} - P_{potential}) \cdot (\sum P_{load})^{-1} \]  

(9)

Where \(P_{load}\) is the peak load demand.

3.4. Economic modeling based on ACS

The annualized cost of the system (ACS) is composed of the annualized capital cost \(C_{cap}\) and the annualized maintenance cost \(C_{main}\) [15]. Note that the replacement costs here equal to zero, as there are not any parts need to be replaced during the lifetime of the system (no batteries). ACS can be represented by equation (10):

\[ ACS = C_{cap}(PV) + C_{main}(PV) \]  

(10)

The annualized capital cost of the PV array can be donated by equation (11) [15]:

\[ C_{cap} = C_{cap} \cdot (i \cdot (i + 1))^{ysys} \cdot ((i \cdot (i + 1))^{ysys})^{-1} \]  

(11)
Where $C_{cap}$ is the initial capital cost of PV the system, US$; $Y_{sys}$ is the PV system lifetime in years; $(i. (i + 1))^N_{sys} \ast \left( (i. (i + 1))^{N_{sys}} \right)^{-1}$ is the capital recovery factor, which is a ratio to calculate the present value of an annuity and $i$ is the annual interest rate. The annual real interest rate $i$ is a factor of the nominal interest rate $i'$ and the annual inflation rate $f$. So, $i$ can be calculated using equation (12):

$$i = i' - f \ast (i' - f)^{-1}$$

The annualized maintenance cost can be represented by equation (13)

$$Camin(n) = Camin(1). (1 + f)^n$$

where $Camain(n)$ is the maintenance cost of the nth year. The initial values of $C_{cap}, Camin, f, i$ and $i'$ can be found in table 1.

### Table 1. The costs and lifetime aspect for the PV system

| Attribute                              | Value          |
|----------------------------------------|----------------|
| Initial capital cost ($C_{cap}$)       | 6500 US$/kW    |
| Maintenance cost in the first year ($Camin(1)$) | 65 US$/kW    |
| Lifetime (year)                        | 25             |
| Interest rate $i'$ (%)                 | 3.75           |
| Inflation rate $f$ (%)                 | 1.5            |

#### 3.5. System optimization based on genetic algorithm (GA)

For optimizing the system GA was used, the system should keep the ACS and LPSP as low as possible, meanwhile, the power output of the system should cover part of the demands during the first peak. To determine the best amount of power need to be generated to accommodate peak demand while keeping the cost as low as possible, another indicator is needed. Equation (7) and (8) are the representative models for potential energy and load demands. By calculating the integration of equation (7) the total amount of potential power can be found, the same way, by integrating equation (8), the total amount of energy needed by the load every day can be found [16]. As this study focuses on peak demand, the integration on the time period where the peak demand occurs which is from 11 to 14 can give the amount of power needed during the first peak demand. According to the Jordanian National Electric Power Company (NEPCO) Annual Report 2015 [17], the average growth in peak demand is 5.4%. Thus, the system should provide at least 5.4% of the current peak load energy to maintain the peak demand at the same level for one year. Therefore, the integration of $P_{potential}$ divided by the integration of $P_{load}$ (the integration of equations (7) and (8)) should be greater or equal to 0.054 as the following formula shows:

$$\int_{peak\ demand\ starting\ time}^{peak\ demand\ end\ time} \text{Pload} \ast (\int_{peak\ demand\ starting\ time}^{peak\ demand\ end\ time} \text{Ppotential})^{-1} \geq 0.054$$

Matlab optimization toolbox was used. The genetic algorithm was the chosen method for finding the best configuration of the solar farm size, where a maximum solar power needs to be generated to cover peak demand with the lowest possible costs. The decision variable is the $P_m$, which represents the maximum system output power. The yearly data of solar radiation, temperature, and load demand was used in the model. The initial system’s assumption will be subject of the following equations and inequalities constrains:

$$\text{Min (LPSP, ACS)}$$

$$\text{Max (Ppotential, Pm)}$$

$$\int \text{Pload} \ast (\int \text{Ppotential})^{-1} \geq 0.054$$

$$\text{Maximum load demand} \geq P_m \geq 0$$
Equations (15) and (16) were the fitness functions in the optimization toolbox, while inequalities (17) and (18) were the constrains functions.

4. Results
The GA approach was applied, and the best optimization was found after 66 iterations, the optimum solar farm size for Amman east power plant peak demand reduction was found to be 255.22 MW. Figure 4 shows the mean score and the fitness value for each generation of the GA until the optimum value was reached after 66 generations produced. The results were tested and a simulation scenario of adding 255.22 MW solar farm to Amman east power plant was done.
The simulation results show that adding a 255.22 MW solar farm will be an effective solution for decreasing the first peak demand, yet the load curve will not become smoother as can be seen in figure 5. The effects of the suggested solar farm will not take any effects before 7:00, where the solar radiation starts to generate a significant amount of energy, before 7:00 the solar radiation is negligible and it would not generate passable energy, thus the load demand curve will stay the same as before adding the solar farm from 19:00 till 6:00.

At 7:00, as the radiation starts to increase, the generation of energy starts as well. The energy generation keeps increasing as the solar radiation will rapidly increase till 12:00, yet the load demand is also growing rapidly to reach the first peak at 11:00. So, the resulting new load demand curve will increase till 11:00, where it reaches its first peak. After 11:00 the new load demand starts to decrease, meanwhile in the original load demand (without adding solar farm) the load will slightly grow after 11:00.
The demand will keep decreasing till 13:00, at 13:00 it keeps almost constant till 14:00. Then after 14:00 it starts to increase quickly till 19:00 where the radiation is too low to generate energy. As it is clear from the new load curve, after adding the solar farm, the new load demand curve has one small peak demand at 11:00, and high peak demand at 18:00. The suggested solar farm would decrease the peak demand, yet it would not make the curve smoother of more flat. Actually, the curve became sharper especially after 14:00. This can be explained by the nature of solar radiation, as showed in the previous sections the solar radiation is stochastic, where the generation peak is much higher than the average generation ratio and most of the high generation occurs in the period 11:00-13:00. That solar radiations’ nature can explain why the solar farm works efficiently during the period 10:00-14:00, but before and after the generation of energy drops fast.

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