Design Optimization of Photovoltaic Arrays on Curved Surfaces

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***Abstract*—Flexible photovoltaic (PV) arrays often have to be mounted on surfaces that have a significant amount of curvature. These include solar-powered vehicles, planes, and also some wearable devices. However, this inevitably leads to non-uniform solar irradiance among connected PV cells. If one cell among series-connected PV cells receives significantly lower solar irradiance, the overall power generation of the string is reduced. While previous works dealt with this by employing sophisticated run-time techniques, we show that design-time approaches that determine the electrical series-parallel connection of a PV array could also significantly enhance the power output. In this paper, we propose a *k*-means clustering-based algorithm to group PV cells/modules with similar solar irradiance to form a PV string, even allowing irregular arrays, to maximize the power generation of the array for a given irradiance profile. Our experimental results show that the power generation of a PV array could be increased by 84% compared to usual PV array organizations that do not take the curvature of the mounted surface into account.**

I. Introduction

Photovoltaic (PV) cells are highlighted as clean and sustainable energy sources for applications at various scales, ranging from energy harvesting sensors/wearable devices, electric vehicles, and even building integrated PVs (BIPV). PVs are useful for prolonging the lifetime of a application especially under situations where there are restrictions on the weight, size, and cost of the application, and batteries cannot be indefinitely included. PVs can supply electrical power consistently to the load as long as there is a light source.

Flexible PVs provide more flexibility to exterior design for gadgets, vehicles, and buildings to allow for comfort, aerodynamics, and aesthetics. Such designs include wearable devices such as wristbands powered by PV cells, ground/aerial vehicles, or buildings and rooftops covered by PV modules. Take rooftop PV arrays for example. While conventional rooftop PV arrays installed on a flat roof with some tilt angle [4], [19] do not allow much room for aesthetics, curved-shape BIPVs enables a trade-off between the form and the function [14]. Integration of PV modules into the building material results in cost reduction as well. Also, in some cases, it might not be possible to install flat PV panels due to various reasons such as weight, cost, form factor, and aerodynamics. Figure 1 shows a solar-powered aircraft from NASA, Helios, where the curvature of the surface on which the solar panels are mounted is significant and clearly visible.

PVs require careful conditioning by the periphery circuits as their power generation depends significantly on the operating voltage and current. They require maximum power point

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Fig. 1. PV panel attached to a plane [11].

tracking (MPPT) to ensure they generate the maximum power according to changing irradiance received by the PV cells. When the PV array is *uniform* in the sense that incidence angles of lights are the same and electrical connection topology of PV cells is regular, MPPT is done with ease and a number of well-established techniques exist [2]. However, maximizing the power generation of a PV array with non-uniform solar irradiance is more demanding. A typical scenario for a PV array receiving non-uniform solar irradiance arises from the partial shading effect, for example on PV arrays mounted on rooftops on or vehicles. Even if only one PV cell in a series-connected PV string receives significantly less amount of solar irradiance, the output current of the whole string is limited by the shaded cell. Sophisticated run-time optimization approaches have been studied for these scenarios [13], [8].

A flexible PV on a curved surface is constantly exposed to non-uniform irradiance as can be inferred from the PV panels in Figure 1. The difference, in this case, to the partial shading effect is the solar irradiance difference among the cells is not as abrupt, but rather follows a smoother spectrum. Also, it is the result of the curvature of the surface, and not the result of nearby obstacles, or dust on the PV panels, which cannot be predetermined and accounted for during design time. We take a cue from this fact that the distribution of irradiance values each PV module receives can be known at design time, and propose to take advantage of it. In this paper, we propose a *design-time* approach to maximize the power generation of a PV array on a curved surface. This is done by *configuring the electrical series-parallel connections* among PV cells/modules considering the solar irradiance they receive. Furthermore, we show that even using irregular arrays, i.e., parallel connection of uneven number of PV strings, could be beneficial. The proposed approach could be applied both at PV module-granularity and PV cell-granularity. If a PV array is installed on a large surface with multiple flexible modules involved, only the wiring among the PV modules could be

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determined during their installation, which would not involve changes in the manufacturing process of PV modules. If the proposed approach is used for small wearable devices, the configuration of electrical connection can be done at the cell-level. In such cases, PV modules should be manufactured with regards to the curvature of the particular application.

The contributions of this paper are summarized as follows.

- This paper, for the first time, introduces a *design-time approach*, which finds the electrical series-parallel connections to deal with the imbalance in solar irradiance, primarily caused by the curvature of the surface on which the PV panels are to be mounted. .
- We devise a *k*-means clustering-based algorithm to group PV cells/modules of similar irradiance, and form a PV array capable of maximizing the power generation.
- The proposed method distinguishes itself from previous reconfiguration-based approaches in that it uses less hardware resources. Basically, the proposed approach does not require any additional active components other than slightly increased wiring complexity.

The rest of the paper is organized as follows. Section II provides the summary of the prior literature on the topic. Section III explains the organization of PV arrays, and their behavior under various irradiance conditions. Section IV introduces the *k*-means clustering-based algorithm, which finds the electrical connection topology that maximizes the power generation. Section V provides the experimental results, and the concluding remarks are given in Section VI.

II. Related Work

Maximizing the power generation of PV arrays inevitably involve MPPT. Various MPPT techniques for finding the optimal operating voltage and current of a PV array have been developed based on hill climbing [18], perturb and observe methods [3], fuzzy network [17], and even neural networks [15]. MPPT is an essential function of PV inverters or DC-DC converters as there could be significant degradation in power without it.

Partial shading has been one of the major causes that reduces the power generation disproportionately. A typical way to handle this problem is to connect a bypass diode in parallel to the PV modules. This provides an alternate path for electrical current when events such as the partial shading effect occurs. Under such circumstances, the voltage-current characteristics become more complicated with local maximums in power generation, and a more sophisticated run-time technique is needed [13], [8]. There has been work to address the partial shading effect by employing reconfiguration techniques [10], [6]. They utilize a three-switch topology, which enables control of the series and parallel electrical connections to cope with the partial shading effect. Reconfiguration has proven to be an useful tool to combat partial shading, but it requires additional electric components and circuitry. While reconfigurable architectures could be also useful for PV arrays on curved surfaces, we find that it would be cost-effective to find a design-time solution. We would like to also point out that our design-time approach and run-time reconfiguration are not contradictory and could be used together, while we leave it as a future work.

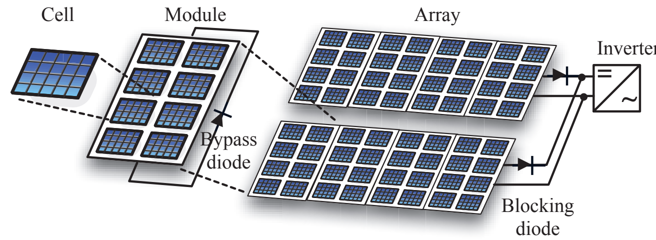


Fig. 2. PV array composition.

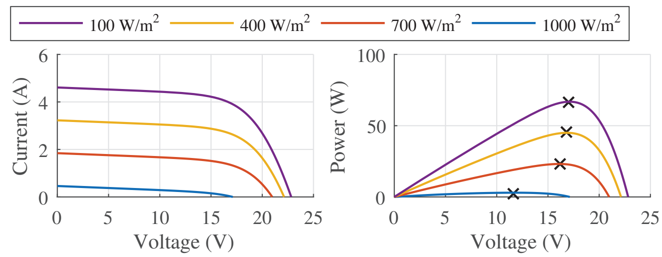


Fig. 3. Voltage-current curve of a PV module according to solar irradiance.

As opposed to these line of works, this paper aims at optimization at design time. This approach makes sense as the physical locations of PV cells are likely to be determined and fixed at design time. The patterns of solar irradiance on to the PV array could be characterized at design time and a solution could also be found at design time.

III. PV Arrays on Curved Surfaces

A. PV Array Composition and Behavior

PV arrays are composed of PV modules, which is again a series connection of PV cells as shown in Figure 2. For example, a 12 V panel would comprise 36 PV cells in series. The PV modules could be connected in series to increase the output voltage, and in parallel to increase the output current. Usually, a bypass diode is placed in parallel to a PV module in order to provide a path for the string current when partial shading occurs. Also, a blocking diode is connected at the terminal node of each PV string, such that the PV modules would not be damaged due to excessive voltage difference among PV strings when events such as partial shading occurs. Typically, a PV array is connected to a single central inverter, or DC-DC converter if the output is DC, which is equipped with maximum power point tracking (MPPT) capability. How an inverter, or a number of inverters connect to the PV array is another line of research topic, where there could be various options including micro-inverter architecture, string inverter, and central inverter [7]. However, this might not be very desirable in a size-, weight-, and cost-constrained applications such as solar planes and wristbands. Hence, we restrict the topology to a central inverter as we are looking for a cost-effective design-time solution.

A PV module follows a voltage-current curve, which changes according to the irradiance level, e.g., 100, 400, 700, and 1,000 W/m^2 in Figure 3. PV current gradually decreases as the operating voltage increases until there is a rapid drop and falls to zero. The maximum power point (MPP), i.e., the operating voltage V_{MPP} and current I_{MPP} changes according to the irradiance levels. I_{MPP} changes significantly while V_{MPP} value only moderately changes. Tracking the MPP is crucial

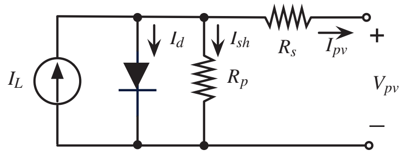


Fig. 4. Equivalent circuit model of a PV module.

for maximizing the power generation. One observation we can make from the figure is that, while the available voltage range does not change dramatically according to solar irradiance, the current range changes significantly. This means that if one PV module in a PV string received significantly lower irradiance than others due to nearby obstacles, dust on the panel, etc., the current through that string would be limited to the module. This forces all the other PV modules to operate far off the MPP and degrades the output power generation of the whole string, and hence, partial shading effect happens.

To be more specific, the PV behavior is usually modeled by the single-diode equivalent circuit model shown in Figure 4 from [16]. The relationship between the voltage and current is usually described by the following equation.

$$\begin{aligned} I_{pv} &= I_L - I_d - I_{sh} \\ &= I_L(G) - I_0(T)(e^{V_{pv}+I_{pv}\cdot R_s)(q/AN_skT)} - 1) - \frac{V_{pv}+I_{pv}\cdot R_s}{R_p}, \end{aligned} \tag{1}$$

where

$$\begin{aligned} I_L(G) &= \frac{G}{G_{STC}} \cdot I_L(G_{STC}), \\ I_0(T) &= I_0(T_{STC})\left(\frac{T}{T_{STC}}\right)^3 e^{(qE_g/AN_sk)(1/T_{STC}-1/T)}. \end{aligned} \tag{2}$$

Symbols I_{pv}, I_L, I_d, I_{sh}, R_p, R_s, and V_{pv} are defined in Figure 4, G denotes the irradiance level in W/m^2, T, the PV cell temperature, q, the elementary charge, E_g, the energy band gap, A, the diode ideality factor, N_s, the number of cell in series, and k, Boltzmann's constant, respectively. STC denotes standard test condition, which is the solar irradiance intensity of 1000 W/m^2. The values of the parameters have been taken from [9].

B. PV Array on Curved Surface

The problem of uneven solar irradiance stemming from PV panels being mounted on curved surfaces, although of practical relevance, have not been well studied until now. There are two main differences between partial shading and a PV array on a curved surface. First, PV cells on a curved surface would have smoother spectrum of solar irradiance intensity, where partial shading results in a group of cells receiving distinctly less solar irradiance while the rest of the cells receive a very similar amount. Second, the pattern of uneven distribution of solar irradiance over time is dependent on the angle a PV cell is facing, not on nearby obstacles where their behavior is less predictable.

From this we can infer the followings. First, optimizing the power generation for a PV array on a curved surface should be done with regards to the continuous spectrum of MPPs of all the cells at the same time, unlike handling the partial shading, which could be managed by excluding a few cells with low irradiance. For example, bypass diodes achieve this by providing an alternative current path and excluding the PV cells. Second, it is better to come up with a design-time solution because the solar irradiance distribution is predictable at design time. Reconfiguration-based approaches are more suitable for dealing with partial shading as shading patterns are hard to predict at design time, and hence, it is worthwhile to invest in flexibility during runtime. Therefore, we propose a design time solution, which involves all the PV modules in a PV array by determining the series-parallel connection with regards to solar irradiance distribution patterns. As we have briefly mentioned in the introduction, the approach could be applied not only at PV module-level, but connection among PV cell could be configured as well, depending on the scale of curvature. For example, electrical connections of a PV module for a wristband could be optimized at cell-level. But, this would require additional efforts when manufacturing the PV module.

We have performed some initial simulations using the PV model to show some examples. Figure 5(a) shows the irradiance distribution of a PV array consisting of 60 PV modules attached on a part of a sphere. It assumes that the light is coming down in right angle. The effective irradiance depends on the incidence angle of each cell. We have calculated the maximum power point (MPP) of each setup. The first setup constructs four PV strings of equal length by connecting physically adjacent modules in series. The second setup again constructs our PV strings of equal length, but by connecting PV modules that have similar effective irradiance. The third setup constructs four PV strings of unequal length, with awareness of effective irradiance. The power generation of each PV array at respective MPP, i.e., 12.2 A, 14.0 A, and 14.5 A, are 2,909 W, 3,112 W, and 3,181 W, respectively. Hence, the power generation of the PV array for this single irradiance value changes by 9.4%, while the improvement over time could be much more significant as we will show in Section V. As the inclination angle of each PV module in a PV array is fixed at design time, the power output of the PV array can be optimized at design time by connecting the PV modules appropriately.

IV. PV Module Grouping Algorithm

In this section, we provide the problem definition, important observations, and based on these, the k-means clustering-based PV module grouping algorithm.

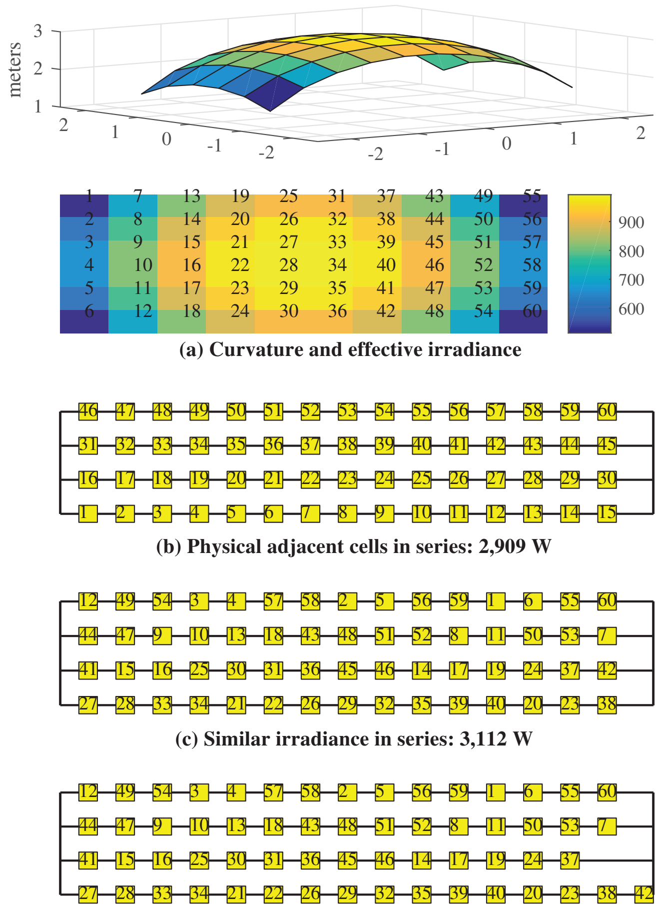
A. Problem Definition

The objective, energy maximization of a PV array on a curved surface, is defined as follows.

Objective: For a PV array comprising m modules from PV_1 to PV_m, where each module comprises again multiple cells as in Figure 2, maximize the energy generated for a period of time, from t_1 to t_2, where the solar irradiance is given as a vector $\vec{G}(t)$ where its magnitude and direction may change over time t. The objective can be written as

$$\max_{config} \int_{t_1}^{t_2} P_{MPP}(\vec{G}(t), config)dt, \tag{3}$$

where $P_{MPP}(\vec{G}, config)$ is the power generation of a PV array under irradiance $\vec{G}$ when the series-parallel connection is



(a) Curvature and effective irradiance

(b) Physical adjacent cells in series: 2,909 W

(c) Similar irradiance in series: 3,112 W

(d) Uneven number of cells in series: 3,181 W

Fig. 5. Different connection examples where the number of PV strings is four.

configured as $config$. A configuration, $config$, is a mapping from the set of PV modules to an integer set $config: PV \rightarrow N$, where $N = \{1, 2, 3, \cdots m\}$. An integer in N corresponds to a PV string, and therefore, maximum number of PV strings would be m, which would mean a fully parallel connection.

Constraints: There is usually a minimum bound on the input voltages of the inverters, V_{min}. In general, increasing the number of PV strings is better for coping with non-uniform solar irradiance. But, this will reduce the total voltage of the PV array, which cannot go below V_{min}. Also, it will increase the current, which means thicker wires are needed. There are electrical constraints of course, related to the model in Section III. The equations (1) and (2) should hold for each PV module, which means the system of equations formed by (1) and (2) should be satisfied at all times unless there is current flowing through the bypass diodes, or a blocking diode blocks current flowing into a string. How we ensure constraints are satisfied will be elaborated in Section V.

B. Observations

In this subsection, we provide some observations that will be exploited for the k-means clustering-based algorithm.

Observation 1: *The operating current of a PV module I_{PV} should be the same as other PV modules within the PV string.*

Hence, it is important that all the PV cells/modules in a PV string should have similar I_{MPP} such that all the cells could operate near the MPP.

Observation 2: *The operating voltage of a PV module, V_{pv} is influenced by number of modules in other PV strings.*

The summation of V_{pv} of all modules in a PV string should be equal to the values of all other PV strings as they are directly connected to each other in parallel. As we have observed from Figure 3, the V_{MPP} is not dramatically different based on solar irradiance values. Hence, the PV array would still remain largely regular, i.e., similar number of PV modules per string. But, it some cases where there is consistent difference in irradiance levels among the PV strings, having uneven number of PV modules per PV string might allow each modules to operate closer to their respective MPP.

C. k-means Clustering-Based Solution Algorithm

Based on the observations from the previous section, we devise an algorithm for finding the PV array configuration. We first lay out the challenges in developing the algorithm.

Challenges: The algorithm should group PV modules in a way that each of them operate close to their respective V_{MPP}, and I_{MPP}. Grouping of PV modules to form PV strings similar to *clustering* with some additional constraints. If the algorithm simply uses existing clustering algorithms and gather cells which have similar I_{MPP}, there is no guarantee that the clusters will be of similar size. In order to ensure that each module operates near V_{MPP}, we should control the size of the clusters as well.

The proposed algorithm shown in Algorithm 1, effectively copes with this issue by imposing cluster size constraints. The inputs to the algorithm are Loc_{pv}, $Norm_{pv}$, $G[t]$, and n_p, which denote an set containing the location of each PV module, a set containing the normal vectors of the planes including each PV module, a set of solar irradiance vectors over time, and the number of PV strings in parallel, respectively. The output of the algorithm is a mapping $config: PV \rightarrow S_{all}$, where PV denotes the set of PV modules and S_{all} denotes the set of PV strings. The algorithm determines which string, s_k, a PV module pv_j should be attached to, and hence, a unique PV array configuration.

The algorithm builds around a widely known clustering method, k-means clustering [5]. The key idea of Algorithm 1 is that PV modules receiving similar amount of solar irradiance over time, are likely to have similar MPP current over time, I_{MPP}. Another major consideration is that the number of PV modules in a PV string should be similar in order to let PV module operate near V_{MPP}.

As an initialization process (lines 1 to 5), an array of effective solar irradiance values, G_{arr} is calculated for the whole PV array. $Garr_{i,j}$ contains effective irradiance received by PV module pv_j at time t_i. Since PV modules are placed on a curved surface, each PV module would have different $Loc_{pv,j}$ and $Norm_{pv_j}$ values. Then, k-means clustering is performed (line 6) to find an initial mapping $config_{init}$, which finds n_p PV clusters, based on *similarity* among irradiance traces of each PV module. The function to calculate the similarity, or distance, between PV modules, **EucDist()**, works as follows. **EucDist()** treats the irradiance values of a PV module pv_j of over time $(Garr_{s,j}, \cdots, Garr_{e,j})$, as a $s-e+1$-dimensional

Algorithm 1: PV Module Clustering Algorithm

Input: Loc_{pv}, $Norm_{pv}$, $G[t], n_p$
Output: $config : PV \rightarrow S_{all}$
1: **for** $t_i \in [t_s, t_e]$ **do**
2: **for** $pv_j \in PV$ **do**
3: $Garr_{i,j} \leftarrow$ **calcGeff**$(G[t_i], Loc_{pv_j}, Norm_{pv_j})$
4: **end for**
5: **end for**
6: $config_{init} \leftarrow k$-**means**$(\{Garr\}, n_p,$ **'EuclideanDist'**$)$
7: $n_{s,target} \leftarrow n_{module}/n_p$
8: $S_{processed} \leftarrow \phi$
9: $H_{string} \leftarrow$ **histogramValues**$(config_{init})$
10: $config \leftarrow config_{init}$
11: **for** $i \leftarrow 1, \cdots n_p$ **do**
12: $j \leftarrow \underset{j \in S_{all} - S_{processed}}{\textbf{argmax}} (h_{string,j})$
13: $S_{processed} \leftarrow S_{processed} \bigcup S_j$
14: $PV_j \leftarrow$ **findPvSet**$(PV \rightarrow S_j)$
15: **while** true **do**
16: **if** $h_j = n_{s,target}$ **then**
17: break
18: **end if**
19: $(k,l) \leftarrow \underset{pv_l \in PV_j, \; s_k \in S_{all} - S_{processed}}{\textbf{argmin}} (\textbf{EucDist}(Garr_{s,\cdots e,l}, cent(s_k)))$
20: $h_j \leftarrow h_j - 1$
21: $h_k \leftarrow h_k + 1$
22: $config.$**transfer**(pv_l, S_j, S_k)
23: **updateCentroid**(S_j, S_k)
24: **end while**
25: **end for**
26: **return** $config$

coordinate, and calculates the Euclidean distance between two PV modules. If the Euclidean distance between two PV modules is small, the likelihood of gathering together into a PV string is increased.

Balancing the cluster sizes: However, the clustering result cannot be used directly because the number of PV modules per cluster could be imbalanced. And as observed in Section IV-B, this would force the PV modules to operate far off from V_{MPP}. So, the next step is to balance the number of PV modules per clusters, i.e., PV strings (line 7 to the end). First, we determine the target number of PV modules per string, $n_{s,target}$ (line 7), analyze the number of PV modules per string (line 9). Then, beginning with the PV string with the largest number of PV modules (string j in line 12), we distribute PV modules in that string (PV_j in line 14), to another string (k in line 19). The criterion for selecting the pair of PV module to be moved out pv_l and the target string k, is the Euclidean distance between *centroid*, i.e., center of target string k in terms of *Garr* coordinates, and pv_l should be the smallest among all possible pairs (line 19). Then, we perform the transfer of the PV module and update the relevant data structures (line 20 to 22). Of course, the centroid of the affected clusters, S_j, S_k should be updated every iteration. There is no guarantee that this heuristic algorithm will produce the optimal solution, but we show in the subsequent section that the algorithm performs quite well. We emphasize that the rationale behind algorithm is that it is I_{MPP}, which is influenced more than V_{MPP} according to solar irradiance, and k-means clustering performs already fairly well in gathering PV modules with sufficient similarity, which guarantees decent performance.

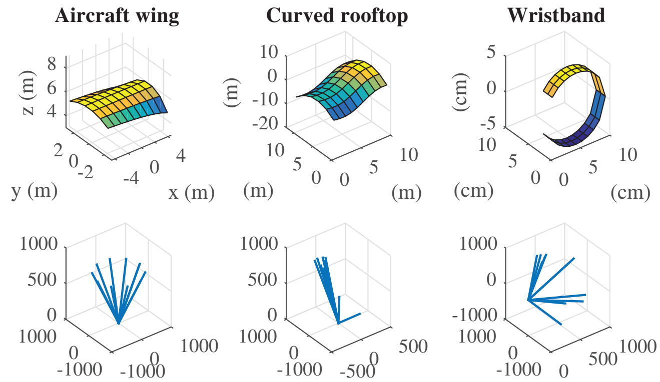


Fig. 6. Three exemplar surfaces and the corresponding irradiance profiles used for the experiments. The lines in the irradiance graphs (bottom graphs) denote the directions to the light source, which changes over time (multiple lines). The surfaces are assumed to be located at (0,0,0). The surface and the irradiance vector in the same column form a pair for an evaluation.

V. Experiments

In this section, we provide performance of the proposed k-means clustering-based algorithm by comparing the total energy generation when given the trace of solar irradiance.

We implemented the PV array model and the proposed algorithm on MATLAB environment. The equations (1) and (2) for each PV module has been formulated as a system of equations to calculate the operating voltage and current values. To find the MPP, we use fmincon function in MATLAB, which uses interior-point algorithm [1].

Figure 6 shows the types of surfaces and irradiance profiles we have used to evaluate the proposed algorithm. We synthetically generate three curved surfaces, each representing an aircraft wing, rooftop of a building, and a wristband. The surfaces do not represent a specific vehicle, building or a product, but we emphasize that we do not lose generality. The physical location and panel angle of each PV cell are considered. Curvature of individual cells also has an impact on the power generation [12], but in this work we assume that the radius of curvature is large compared with the cell sizes and ignore the intra-cell curvature. The irradiance vector over time for the aircraft wing surface, assumes that the elevation angle of the sun in high, and the aircraft is making a circular maneuver. The vector for the curved rooftop assumes that the relative position of the sun is moving as the earth rotates. But still, the sun light is coming mainly from the $-x$ direction. The vector for the wristband scenario assumes that the body is located at $-x$ direction, such that the sun light is mainly coming from $+x$ direction, but in a more random manner. For the first two scenarios, we assume a PV module-level application of the algorithm, while for the last one, we assume a PV cell-level application of the proposed algorithm.

First, we show the results of the k-means clustering algorithm compared with the baseline where physically adjacent PV cells/modules are grouped together. Figure 7 shows the result of clustering for an example for 60 PV modules of *aircraft wing* case. It is clearly visible that the clustering results from the proposed algorithm performs better in grouping the PV modules with similar irradiance values. As this enables all the PV modules to have similar I_{MPP} values, and hence, increase the power output as can be seen from below.

More detailed results are shown in Figure 8. The difference in voltage of the PV array is small compared with the

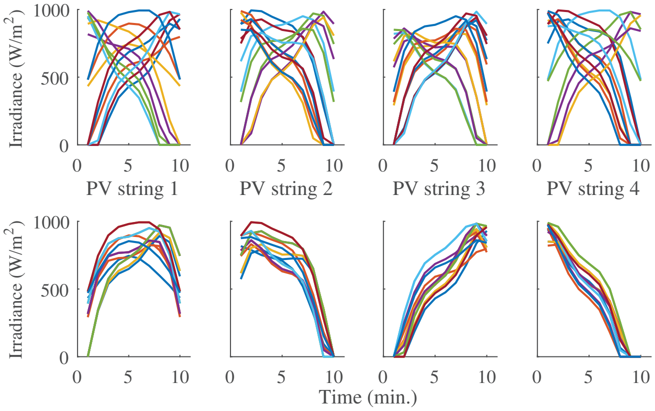


Fig. 7. Solar irradiance value of PV modules over time grouped into four PV strings for the aircraft wing case. Top four graphs are from physically adjacent grouping, and bottom four are from the proposed clustering algorithm. Each line in a graph denote solar irradiance trace over time for a PV module in the string.

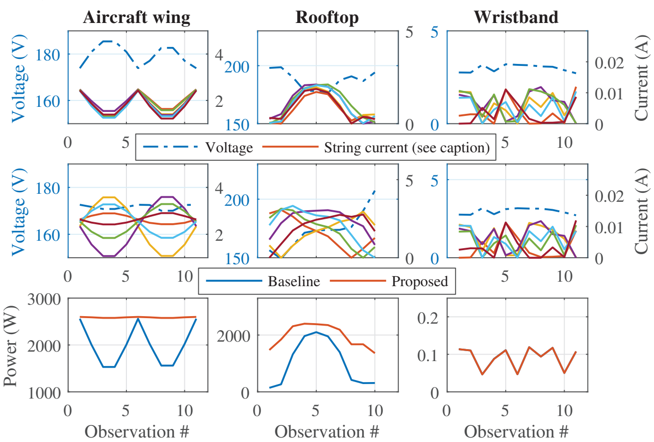


Fig. 8. Total voltage of PV array, string-wise current, and power generation of observations over time. Each solid line in the graphs of the first two rows denotes the current of a PV string over time. The graphs in the first and second row are from the baseline algorithm, and the proposed algorithm, respectively.

differences between PV string currents. If you see the aircraft wing scenario (leftmost column), bad clustering of the baseline algorithm (uppermost row) results in PV modules receiving high irradiance forced to generate low current. The proposed algorithm performs a better clustering, and PV strings receiving more irradiance in general will be able to generate higher current (middle row). This leads to higher average power generation (bottom row). Average power generation resulting from the baseline algorithm for aircraft wing scenario is 1,936 W, while the proposed algorithm results in 2,586 W. The same explanation holds for the curved rooftop scenario. The baseline results in 1,106 W, while the proposed algorithm results in 2,034 W, an improvement of almost 84%. The case for the wristband is somewhat different. In this case, the baseline, which groups physical adjacent PV cells together, works quite well. The proposed algorithm has not much room to improve over the baseline, and the difference in power generation is negligible. The amount of gain depends largely on the specific shapes of the curvature, and the solar irradiance patterns, but we observe significant potential in power generation by the proposed approach.

VI. Concluding Remarks

This paper proposed a design-time solution, for the first time, to handle non-uniform solar irradiance that a PV array receives due to the curved surface on which it is placed. Our technique considers the serial-parallel connections of a PV array as a control variable, and an algorithm is devised based on *k*-means clustering method. The average power output is increased by up to 84%. Compared with previous approaches such as dynamic reconfiguration, which does not make use of information available at design time, we reiterate that the proposed approach makes use of the correlation of solar irradiance values among each cell, which can be inferred from the curvature. In fact, dynamic reconfiguration could be used together with this approach. Optimization dealing with the wiring harness or joint optimization with dynamic reconfiguration remains as a future work.

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