Fundamental Evaluation of Data Clustering Approaches for Driving Cycle-Based Machine Design Optimization

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***Abstract*— This article presents a fundamental evaluation of different clustering methods for analyzing driving cycles toward the efficient design of electric machines. It uses clusters of operating points to identify representative points (RPs) and the related optimization weights to design electric machines with optimal efficiency in the specific operating range. Typically, the design optimization of machines is carried out for one or a few speed–torque points. This article shows that for a predictable driving cycle or a specific set of operating points on the torque–speed plot, cluster analysis can be used to determine the representative operating points, which can be utilized in the optimization process to improve the overall efficiency for the considered driving cycle or operation profile. Furthermore, if multiphysics design is considered, the machine performance metrics can be guaranteed in multiple domains. This article presents a review of data clustering methods and their application in machine design optimization, where the pros and cons of the methods are weighed up. Further, X-Means method is proposed as an automated approach for cluster analysis and identification of RPs. In order to assess the effectiveness of the proposed method, a case study is carried out for the electromagnetic design of an interior permanent magnet (IPM) machine for the World-wide harmonized Light vehicles Test Procedure (WLTP) driving cycle.**

***Index Terms*— Clustering methods, electric machines, optimization methods, permanent magnet machines, traction motors.**

I. Introduction

As THE usage of electric and hybrid vehicles continues to grow globally and sales are expected to reach 38% of the global vehicle sales in 2025 [1], the electric motor is still being considered to be one of the key elements in the powertrain of the hybrid and electric vehicles, and several researchers have focused on the optimization of the electric machine design to meet the powertrain efficiency requirements and overcome the challenges related to cost, size, and weight.

Generally, the optimization of the machine design for an electric vehicle can be based on a single or a few operating points of the torque–speed profile, which would guarantee acceptable performance characteristic at those specific points. Depending on the driving cycle of the vehicle or the application, the electric motor operating range would include several torque–speed operating points. Optimizing the machine design for a single operating point might not ensure that the efficiency and other performance indices are within the design requirements for all the operating points within the considered driving cycle. Accordingly, including more driving cycle points in the design optimization process can enhance the overall performance of the machine and the driving cycle efficiency for all the torque–speed range of operation. Furthermore, for design optimizations that involve multiphysics constraints in addition to the electromagnetic requirements, an increased number of considered operating points would enhance the flexibility to adapt the optimization to the significance of each point in the considered domains.

Typically, the design of the electric traction motor is focused on satisfying acceleration, passing, and grade launch requirements [2]. However, the design requirements can go beyond the electromagnetic properties and depend heavily on the application, which is defined by the driving cycle and operating conditions. Therefore, any design optimization framework should consider several aspects, such as torque–speed characteristics, thermal behavior, efficiency, electromagnetic compatibility, noise and vibration behavior, spatial limitations, and production cost. Since the motor performance can vary based on the operating point, meeting the design criteria and requirements cannot be guaranteed. The clustering analysis can allow a systematic approach of adopting most of the mentioned automotive design criteria in the machine design optimization while considering the whole expected range of operation in the driving cycle.

Optimization of machine design and power electronic control can involve the simulation of thousands of designs, which makes the inclusion of more driving cycle operating points very time-consuming with a significant increase in computational cost and complexity. By considering fewer operating points, which are referred to as representative points (RPs), to represent the driving cycle and the application torque–speed profile, optimization can be performed on these points to enhance the overall cycle efficiency at different torque–speed points. The significance of choosing the number and values of the RPs lies in balancing the gains from including more points

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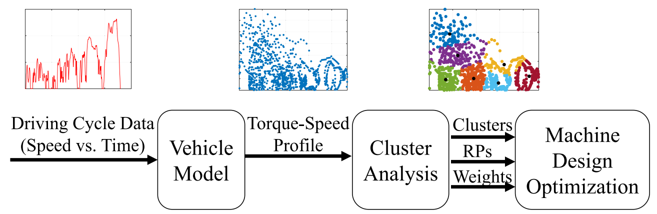

Fig. 1. General approach for machine design optimization using the driving cycle analysis.

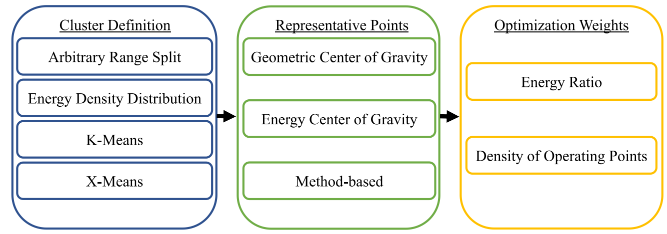

Fig. 2. Overview of the methods used in the cluster analysis of driving cycles.

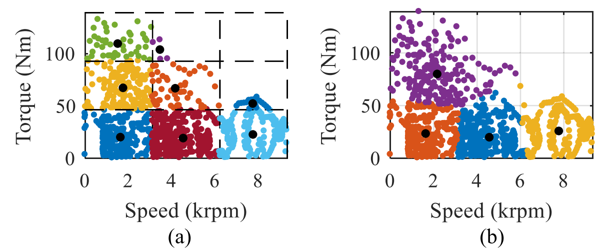

Fig. 3. Torque–speed profile clustering using (a) arbitrary range split and (b) K-Means algorithm.

in the design simulations and, hence, a better depiction of the driving cycle and the downside of increasing computational cost and complexity.

For automotive applications, clustering methods can be applied to split the torque–speed plane into different groups considering the position and density of the operating points on the plane. This is related to how frequently the motor is going to be operated in that specific region. The determination of clusters and RPs can be done in several ways and can be related to different definitions of clusters, qualities that qualify specific points to belong to a given cluster, and the appropriate number of clusters. This approach can, therefore, be used to develop a systematic approach to analyze the specific driving cycles of interest toward obtaining reproducible results.

Cluster analysis is a primary method in data mining. It can be used as a tool to get insight into the distribution of a data set or as a preprocessing step for other algorithms operating on the detected clusters [3]. The underlying principle in cluster analysis is to find groups of data objects, where the objects in a group are related to one another such that they can be distinguished from the objects in other groups. Data clustering can be partitional, where the data objects are divided into nonoverlapping clusters, or hierarchical, where the data objects are arranged in a set of nested clusters as a hierarchical tree.

The conventional approach for driving cycle analysis in machine design optimization is shown in Fig. 1. Typically, the torque–speed profile of the electric motor is obtained from the (speed versus time) driving cycle data using the vehicle or application model, and then, the clusters and the number of operating points are determined using clustering analysis to be used for design optimization.

This article evaluates the effectiveness of different clustering approaches to analyze the driving cycle and determine clusters, RPs, and optimization weights. It also identifies the pros and cons of the data clustering methods toward application in machine design optimization. Based on the analysis, this article also proposes the use of X-Means method as an automated approach to determine the clusters and RPs of the torque–speed profile. A case study is performed on the Worldwide harmonized Light vehicles Test Procedure (WLTP) driving cycle to evaluate the effectiveness of the proposed method for driving cycle analysis for machine design optimization.

In this article, a review of the clustering methods for driving cycle analysis and the proposed X-Means method are presented in Section II. In Section III, the advantages and shortcomings of the clustering methods are discussed. The effectiveness of the proposed algorithm is evaluated with a case study presented in Section IV.

II. Cluster Analysis of Driving Cycles

Several fundamental concepts and definitions need to be described in order to choose the appropriate clustering technique for the drive cycle analysis, as shown in Fig. 2.

A. *Overview of Approaches for Cluster Definition*

Several techniques can be used to group the torque–speed data points of a driving cycle in clusters, some of these techniques are based on data-mining science and others are based on prior knowledge and experience of the application. RPs for the driving cycle are determined based on the defined clusters. The number of clusters resulting from the analysis will define the number of RPs to be used in the motor design optimization, which is significant since it presents the tradeoff between the computational cost and the resulting driving cycle efficiency. Methods for cluster identification can be categorized as the following.

1) Arbitrary Range Split: The method is based on splitting the speed range and torque range, which results in rectangular clusters having a combination of different torque and speed levels [4]–[8], as shown in Fig. 3(a). Dividing the torque–speed plane automatically defines the number of clusters.

2) Energy Density Distribution: According to torque and speed fluctuations in the driving cycle, motor energy distribution for each operating point can be calculated [9]–[12]. Based on the variation of the motor energy on the torque–speed plane, the operating points with significantly higher energy consumptions are considered as RPs. For the rest of operating points, the torque–speed plane is segmented into different clusters, where the number of clusters is determined by comparing the energy loss of all operating points against the loss calculated from the RPs, using a predetermined efficiency map.

3) K-Means Algorithm: K-Means is an unsupervised machine learning algorithm and one of the popular methods for cluster analysis in data mining [13]. The approach is related to partitional clustering, where each cluster is associated with a centroid.

The operating points are clustered into k clusters in which each point belongs to the cluster with the nearest centroid, as shown in Fig. 3(b). The algorithm aims to minimize the objective function set for n data points and k clusters, as shown in the following equation:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \tag{1}$$

where $\|x_i^{(j)} - c_j\|^2$ corresponds to the distance between the data point $x_i^{(j)}$ and the centroid of cluster j and c_j.

The centroids' position on the torque–speed plane is determined iteratively, in two steps: *assignment* and *update*. First, the centroids are initialized randomly, in the assignment step, and each data point, x_i, is assigned to the nearest centroid, c_j, of the cluster S_j, as shown in (2). In the update step, the centroids' positions are adjusted to match the means of the data points within their cluster, as shown in (3) [14]

$$S_j^{(t)} = \left\{ x_i : \left\| x_i - c_j^{(t)} \right\|^2 \leq \left\| x_i - c_j^{(t)} \right\|^2 \forall j, 1 \leq j \leq k \right\} \tag{2}$$

$$c_j^{(t+1)} = \frac{1}{\left| S_j^{(t)} \right|} \sum_{x_i \in S_j^{(t)}} x_i \tag{3}$$

where t is the iteration number.

The two steps are repeated iteratively until the algorithm converges, which when the assignments no longer change.

The K-Means method has been extensively used in electric machine design optimization [15]–[20]. As mentioned earlier, the number of clusters k has must be specified beforehand. Typically, more clusters capture more of the dynamics within the driving cycle at the expense of an increased computational cost of design optimization.

4) X-Means Algorithm: X-Means clustering has not yet been used in electric machine design effectively but can be very effective toward developing an automated, systematic clustering technique for driving cycle analysis. This approach is a variation of K-Means clustering, where cluster assignments are refined by repeatedly subdividing the data points, and keeping the best resulting splits, until a criterion, the Bayesian information criterion (BIC), is reached, as shown in (4) [21]. The approach uses a local BIC score to decide on keeping a split and a global BIC score to decide the final number of clusters

$$\mathrm{BIC}(M_j) = \hat{l}_j(D) - \frac{k}{2} \log(n) \tag{4}$$

where M_j corresponds to models of different number of clusters, $\hat{l}_j(D)$ is the maximum log-likelihood of the data D, and k is the number of clusters. The algorithm is initialized with a minimum number of clusters and centroids as needed until it reaches the upper bound. The centroids with the highest scores are chosen as the final output of the algorithm.

As mentioned earlier, the importance of the number of clusters or RPs was shown to be an important parameter since it affects the optimization results and the computational cost. The method provides a systematic approach, compared to the arbitrary range split, energy density distribution, and visual inspection methods. Furthermore, the optimum number of RPs is determined within the X-Means algorithm and would not require the user to select it as in the case of the K-Means algorithm. The X-Means method can be used to perform clustering, calculate RPs, and also determine an appropriate number of clusters. All three steps can be completed in a single systematic algorithm without user interference and judgment.

B. Determination of RPs

Determining RPs for clusters is an important aspect in the analysis of a given driving cycle since the motor design is optimized based on these torque–speed values. Several methods can be employed toward this task.

1) Geometric Center of Gravity (GCG): The RPs in the cluster i, $T_{\mathrm{RP},i}$, and $\omega_{\mathrm{RP},i}$ are based on the average torque and speed of the points, as shown in the following equation:

$$T_{\mathrm{RP},i} = \frac{\sum_{j=1}^{N_i} T_{j,i}}{N_i} \tag{5}$$

$$\omega_{\mathrm{RP},i} = \frac{\sum_{j=1}^{N_i} \omega_{j,i}}{N_i} \tag{6}$$

where N_i is the number of operating points in cluster i.

2) Energy Center of Gravity (ECG): This method is based on the energy distribution of the points within a cluster, the energy, E_i, of the ith cluster is calculated using the following equation:

$$E_i = \sum_{j=1}^{N_i} E_{j,i}. \tag{7}$$

The calculated RPs, $T_{\mathrm{RP},i}$, and $\omega_{\mathrm{RP},i}$ are given by the following equation [9]:

$$T_{\mathrm{RP},i} = \frac{1}{E_i} \sum_{j=1}^{N_i} E_{j,i} T_{j,i} \tag{8}$$

$$\omega_{\mathrm{RP},i} = \frac{1}{E_i} \sum_{j=1}^{N_i} E_{j,i} \omega_{j,i}. \tag{9}$$

3) Method-Based Approaches: For some clustering methods, cluster definition and the RPs calculation are performed implicitly within the algorithm. This approach includes methods, such as K-Means and X-Means, which have been described in Section II-A.

C. Design Optimization and Weight Assignment

In order to account for the significance of each of the RPs, weights need to be assigned for each of the points to be used within the design optimization process. The weights associated with each of the operating points reflect the energy throughput and the frequency of occurrence. Weights for the RPs can be calculated as a ratio of the energy consumed by all points in each cluster to the total energy consumed in all cluster, as shown in (10). In this method, weights account for the frequency of occurrence and the energy level. In addition, weights can also be calculated based on the ratio of the number of points within a cluster to the total number of operating points of the driving cycle, as shown in (11)

$$W_{E,i} = \frac{E_i}{\sum_{j=1}^{k} E_j} \tag{10}$$

$$W_{F,i} = \frac{N_i}{\sum_{j=1}^{k} N_j}. \tag{11}$$

The weight factors are included in the objective function of the optimization. The objective function is presented as the weighted sum of the objective evaluated at every single RP, as shown in the following equation:

$$F = \sum_{i=1}^{m} \sum_{j=1}^{k} w_j \cdot f_{i,j} \tag{12}$$

where $f_{i,j}$ is the ith optimization objective evaluated at the jth RP, w_j is the optimization weight, m is the number of optimization objectives, and k is the number of RPs.

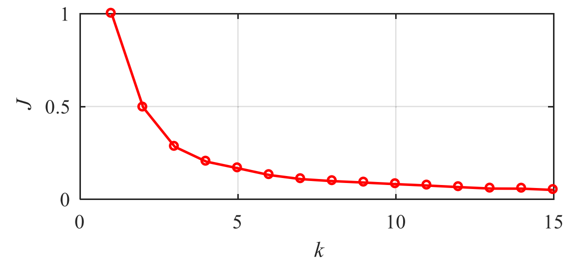

Fig. 4. Elbow method to determine the number of clusters and RPs.

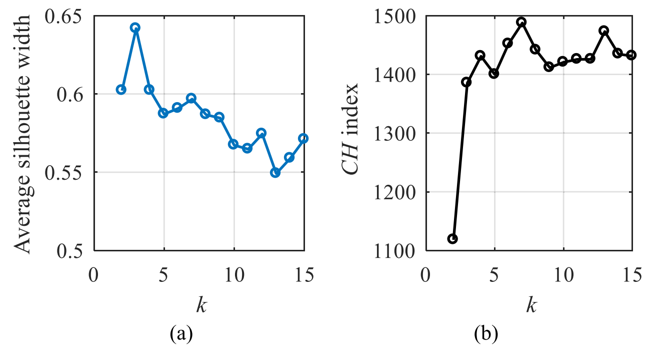

Fig. 5. (a) Silhouette analysis. (b) Calinski and Harabasz index.

III. Discussion and Comparative Evaluation

This section discusses the advantages and shortcomings of clustering methods based on a detailed review of the current literature.

Aside from the methods based on visual inspection of the torque–speed plane [22], [23], the arbitrary range split technique used in [4]–[8] provides a simple way to carry out the clustering. Splitting the torque and speed ranges into equal intervals does not provide the flexibility in clustering the operating points based on their distribution density on the plane. Moreover, the number of clusters determined by the number of intervals in each range might not be optimal. Lazari *et al.* [9], Sarigiannidis *et al.* [10], Chen *et al.* [11], and Jung *et al.* [12] used the variation of the motor energy on the torque–speed plane to define the clusters, and this method would allow adapting the cluster sizes and position on the plane to the distribution of operating points, However, this approach is still not systematic and often relies on user-judgment and visual inspection for the choice of the clusters and RPs. As explained earlier, the number of clusters and RPs are decided using an iterative energy loss calculation. The number of RPs is chosen by the user to minimize the difference between energy loss calculations using RPs and all operating points of the driving cycle. In this method, the goodness of cycle representation is related to energy calculation based on a predetermined efficiency map, which can be different than the actual map. In many cases, the method results in a relatively large number of RPs, which increases the computational cost.

The systematic approach and the simplicity of the K-Means used in [15]–[20] and the methods based on minimizing the Euclidean distance [24] can be appealing for the clustering of the driving cycle points. However, the K-Means has some shortcomings, especially when the clusters are of different size and densities. Furthermore, the number of clusters k has to be chosen by the user; however, the basis for the choice of the value of k was not provided in [15]–[19] and [24]. In [20], the number of clusters was determined using the elbow method.

The elbow method can be used to estimate an appropriate value of k. In the elbow method, K-Means clustering is implemented on the data set for a range of values of k, where J is calculated for each value of k, as shown in (1). The appropriate value of k is chosen based on a plot of J, as shown in Fig. 4. Since the K-Means tends to minimize the variation within the cluster, the objective function J is going to decrease as k increases. The monotonic decrease can make it challenging to determine the number of clusters. Furthermore, the curve may not show any elbow or an obvious point where the curve starts to level.

Based on this analysis, the elbow method can be defined as a measure of the intracluster variation. On the other hand, other data mining methods can evaluate both the intercluster and intracluster variations, which compares the tightness of the points within a cluster with the separation of the clusters from each other. Examples of these methods are the silhouette analysis [25] and the Calinski and Harabasz index [26]. Fig. 5 shows the average silhouette value and the CH index calculated for a torque–speed profile of a driving cycle, using the silhouette analysis and the Calinski and Harabasz index, respectively. Ideally, the maximum value of both indices corresponds to the appropriate number of clusters.

As mentioned earlier, the number of clusters or RPs is an important parameter since it affects the optimization results and the computational cost. The X-Means approach can be seen as a strong candidate toward developing automated data clustering algorithm. The method provides a systematic approach, compared to the arbitrary range split, energy density distribution, and visual inspection methods. Furthermore, the optimum number of RPs is determined within the X-Means algorithm and would not require the user to select it, as in the case of the K-Means algorithm. In addition, it does not need any supporting methods (the elbow method, silhouette analysis, and CH index) to determine the number of RPs, which might not be definite on the appropriate number of RPs and would require user judgment.

Among the methods of RPs calculation for the defined clusters, the ECG method used in [6], [7], [9], [11], and [17] is more efficient compared to the GCG [4]–[5], [8]. This is because it considers the energy weight of the data by positioning the RP closer to regions with higher energy consumption. This is critical for the machine loss minimization across the entire driving cycle.

Similar weights can be assigned to the RPs of each cluster based on both the energy levels and the density of operating points within a cluster. The approach used in [5], [9]–[11], [15], [17]–[18], and [20] biases the machine design optimization toward an enhanced overall driving cycle efficiency. On the other hand, considering the density of points within the cluster [4], [7] can be used to optimize the design objectives to enhance specific metrics of performance in different multiphysics domains, including the thermal and structural domains.

Other well-known clustering methods can be applied in electric machine design. These methods are like the density-based algorithm DBSCAN that allows the identification of arbitrarily shaped clusters and fuzzy C-Means method, where the operating points can belong to more than one clusters. However, the capabilities of these methods may exceed the requirements for the application of driving cycle analysis and can add complexity to the design optimization process.

IV. Design Optimization of IPM Traction Motor: A Case Study

This section evaluates the significance of the number of RPs in the main outcomes of the optimization process' performance of the optimized design across the driving cycle and corresponding computational time and cost. The goal of this case study is to evaluate the effectiveness of X-Means and K-Means as a systematic solution methodology and to compare them to single RP optimization. In the case of the X-Means, the number of RPs is determined implicitly within the algorithm, while for K-Means, the user is expected to provide the number of clusters.

A. Target Motor and Optimization Settings

The target machine for this case study is a 48-slot 8-pole interior permanent magnet (IPM) machine with rectangular NdFeB magnets (N30EH). The motor utilizes an integral slot distributed stator winding, with a slot fill factor of 42%. The maximum peak current density of the stator is set to 20 A_{pk}/mm^2. The machine volume is similar to a WFSM prototype designed and tested in [27], as shown in Table I. The stator outer diameter and stack length are fixed at 254 and 106 mm, respectively. A stochastic differential evolution algorithm is used for the optimization [28] to minimize the machine losses in the optimization tool used in [29]. Commercially available software FEMM was used for electromagnetic simulations, as shown in Fig. 6. The optimization includes 12 stator and rotor geometric factors to govern the dimensions shown in Fig. 7 and Table II, with constraints on torque ripple [30]. The core losses in the stator and rotor pole face are estimated using modified Steinmetz and CAL2 loss models [31]. Toward the calculation of copper loss, high-frequency effects have been ignored in this study, and only dc resistance of the conductors has been considered. Based on this assumption, for the same current

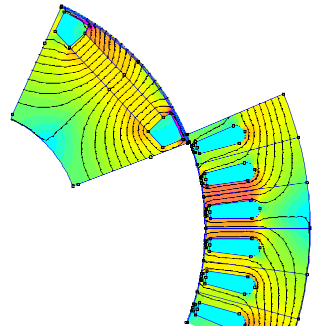

Fig. 6. FEMM electromagnetic simulation of IPM.

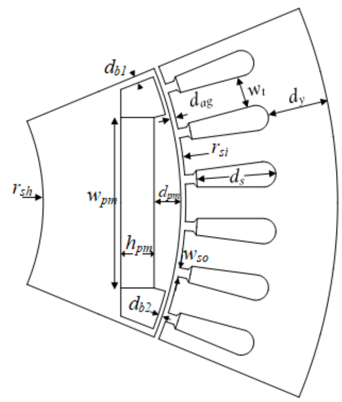

Fig. 7. Parameterized model of the considered IPM.

TABLE I
Motor Parameters and Constraints

Name	Value
Outer diameter	254 *mm*
Stack length	106 *mm*
Stacking factor	0.97
Stator slot fill factor	0.42
DC Bus voltage	600 *V*
Max peak current density	20 *A/mm²*
Operating temperature	100 *°C*

TABLE II
MOTOR DIMENSIONS CONSIDERED IN THE OPTIMIZATION

Symbol	Description	Symbol	Description
r_{si}	Stator inner radius	r_{sh}	Shaft radius
d_y	Stator yoke thickness	d_{pm}	PM depth
d_s	Stator slot depth	h_{pm}	PM thickness
w_t	Stator tooth width	w_{pm}	PM width
w_{so}	Stator slot opening	$d_{b1,2}$	Rotor flux barrier depths
d_{ag}	Airgap length		

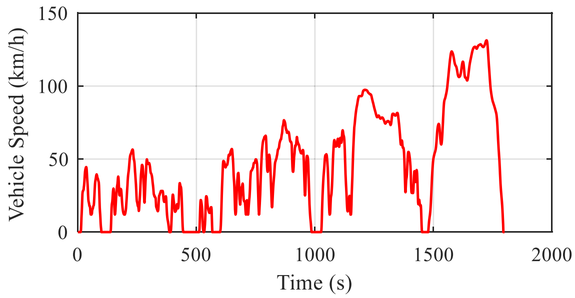

Fig. 8. WLTP driving cycle speed profile.

TABLE III
WLTP CHARACTERISTICS

Name	Value
Duration	1800 *s*
Stop Duration	235 *s*
Distance	23.3 *km*
Average Speed	46.5 *km/h*
Maximum Speed	131.3 *km/h*

density and effective copper winding area, the wire gauge does not change the estimated copper loss. The wire gauge and number of strands per turn can be chosen to achieve the assumed stator slot fill factor and the effective copper area. The same method of loss calculation is used for all three cases in the study. The rated power of the machine determined from the profile envelope is 58 kW, and the constant power speed range (CPSR) is 2.5, with a maximum speed of 10 krpm.

B. Cluster Analysis

The WLTP is considered for this study, as shown in Fig. 8. The driving cycle is used to determine the energy consumption, electric range, and CO_2 emissions for light-duty vehicles [32]. The characteristics of this driving cycle are summarized in Table III.

Using the method presented in [33], the torque–speed profile was identified, as shown in Fig. 9. Assuming a flat road, the traction force in the motor operation can be determined by estimating the rolling resistance and the aerodynamic drag using the vehicle specifications, as shown in Table IV.

The clusters and RPs determined by the X-Means are shown in Fig. 10. The optimization was repeated for a single

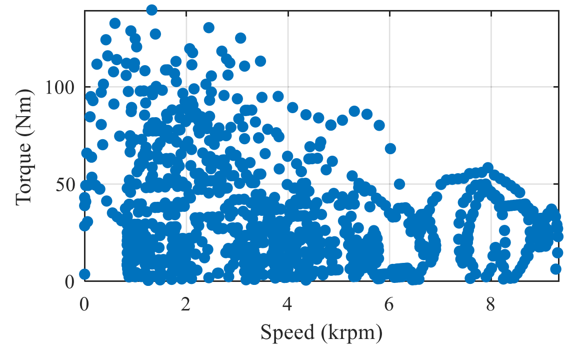

Fig. 9. WLTP torque–speed profile.

TABLE IV
VEHICLE SPECIFICATIONS

Name	Value
Vehicle mass	1800 *kg*
Tire diameter	0.46 *m*
Frontal area	2.22 m^2
Coefficient of aerodynamic resistance	0.22

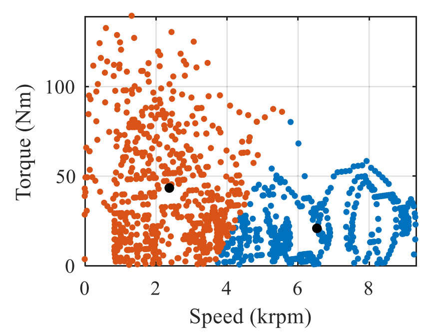

Fig. 10. Clusters and RPs using X-Means.

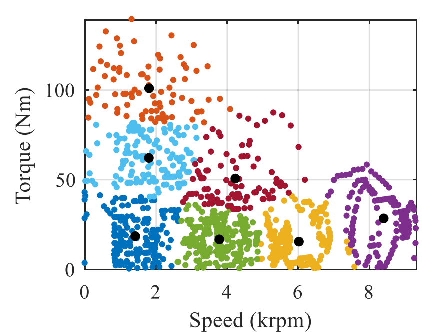

Fig. 11. Clusters and RPs using K-Means.

operating point (rated torque and base speed) and seven RPs determined by the K-Means algorithm, as shown in Fig. 11.

Each optimization consisted of 50 generations, where each generation included 96 members.

Table V shows the RPs values and their associated optimization weights, $W_{E,i}$, that were calculated using (10).

TABLE V
RPs DETERMINED USING X-MEANS AND K-MEANS

X-Means RP			
	Speed (rpm)	Torque (Nm)	Weight, $W_{E,i}$
RP 1	6557	20.4	0.524
RP 2	2398	42.9	0.476
K-Means RP			
	Speed (rpm)	Torque (Nm)	Weight, $W_{E,i}$
RP 1	3775	16.5	0.106
RP 2	8419	27.8	0.291
RP 3	1423	17.8	0.033
RP 4	4323	49.4	0.178
RP 5	1801	99.8	0.118
RP 6	6020	14.8	0.157
RP 7	1871	61.2	0.117

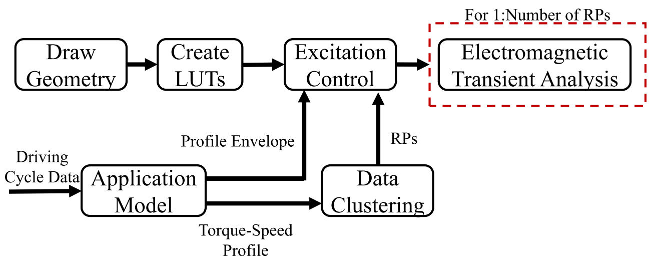

Fig. 12. Excitation control procedure.

C. Electromagnetic Simulation Procedure

In order to develop an optimization framework across multiple operating points with variable dimensional factors and current densities, the simulation steps used is shown in Fig. 12. For each design candidate with a specific PM thickness and stator winding area, the operating points can be attained with different values of current densities and phase advance angles; at the same time, the maximum terminal voltage, which is determined by the dc bus voltage, should not be exceeded.

The FE simulations are used to determine the torque and the magnetic flux linkage values, λ_d and λ_q at the mentioned current densities and angles. The terminal voltage calculation considers the induced voltage and the voltage drop in the armature resistance R_a. Accordingly, two lookup tables (LUTs) were developed, using the FE simulations results and the following equations:

$$T = \frac{3}{2}p(\lambda_d I_q - \lambda_q I_d) \tag{13}$$

$$v_q = R_a I_q + \omega\lambda_d \tag{14}$$

$$v_d = R_a I_d - \omega\lambda_q \tag{15}$$

$$v = \sqrt{v_q^2 + v_d^2} \tag{16}$$

where p is the number of the motor pole pairs, I_d and I_q are the d and q components of the stator current, and ω is the electrical excitation frequency.

The torque levels (T) and the stator voltages (v) are calculated for different values (four values) of stator current densities σ_s and stator current advance angles γ (five values). A few simulations were performed to determine the number of points (σ_s and γ) at which the LUTs are identified. A number of σ_s and γ combinations were simulated at one operating point, and the resulting MTPA current density $\sigma_{s,\text{MTPA}}$ was determined. Increasing the number of the angles and current densities will enhance the accuracy and allow the LUT to find the minimal current density satisfying the MTPA control and the operating point conditions. Although this process is performed once for each design, it has to be repeated for all designs, which could increase the computational cost. Table VI and Fig. 13 show how $\sigma_{s,\text{MTPA}}$ identified by the LUTs can change with different number of σ_s and γ combinations. Accordingly, identifying the LUTs using four and five values for σ_s and γ, respectively, presents a tradeoff between accuracy and computational cost.

Figs. 14 and 15 show normalized values of the electromagnetic torque and magnetic flux linkage of one design for

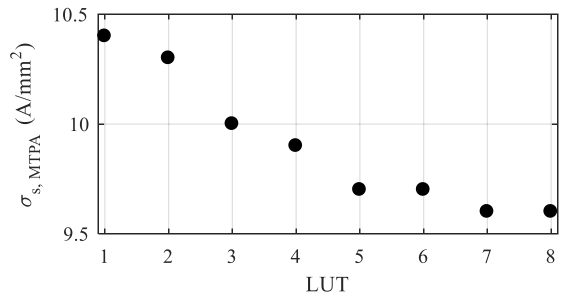

Fig. 13. Identified $\sigma_{s,\text{MTPA}}$ using a different number of σ_s and γ.

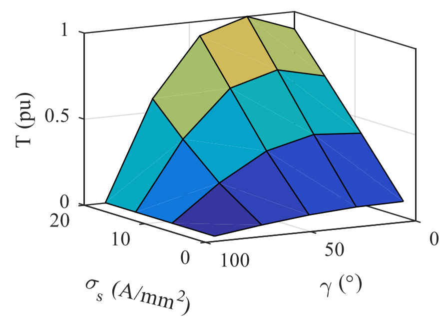

Fig. 14. Normalized electromagnetic torque for a range of current densities and angles.

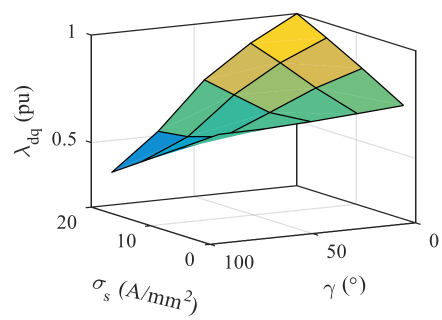

Fig. 15. Normalized magnetic flux linkage for a range of current densities and angles.

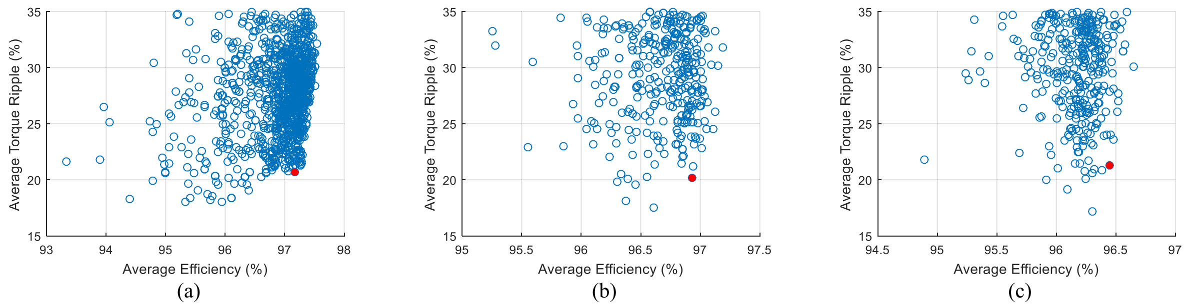

Fig. 16. Optimization members and selected design (shown in red) for optimization. (a) Single point. (b) X-Means. (c) K-Means. Only the members with torque ripple less than 35% are shown.

TABLE VI
IDENTIFIED $\sigma_{s,\mathrm{MTPA}}$ USING A DIFFERENT NUMBER OF σ_s & γ

LUT	σ_s values	γ values	Identified $\sigma_{s,MTPA}$ (A/mm^2)
1	2	3	10.4
2	3	3	10.3
3	4	3	10.0
4	3	4	9.9
5	4	4	9.7
6	3	5	9.7
7	**4**	**5**	**9.6**
8	5	5	9.6

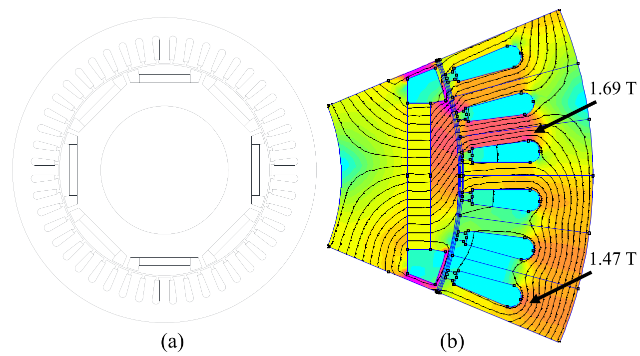

Fig. 17. Selected design from the X-Means optimization. (a) Cross section. (b) Magnetic flux density map.

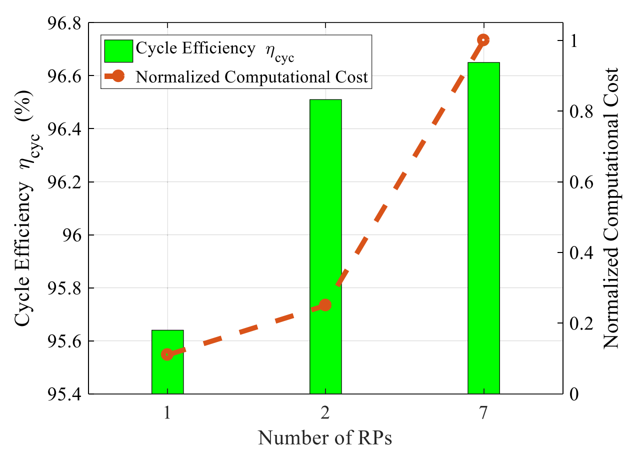

Fig. 18. Optimizations results and computational cost.

different electrical excitation, which will be used in the LUTs. The first LUT (LUT-T) will be used to determine the current magnitudes and angles, which satisfies the torque requirement. The second LUT (LUT-V) will be used to determine the terminal voltage for the corresponding current magnitude and angle.

It must be noted that LUTs do not need to be identified for each operating point for a given design. Instead, the same LUTs are used for all operating points. An initial check is performed to verify that the considered design can attain the profile envelope within the current and voltage requirements. For operating points below or equal to base speed, the current magnitude and angle can be determined using a simple MTPA search algorithm. In the constant power region, where the speeds are higher than the rated speed, the flux-weakening operation should be implemented. A minimum value of the electrical excitation is chosen to satisfy the torque and voltage requirements of the operating points.

D. Optimization Results

A single design was selected from each of the three optimizations, as shown in Fig. 16, and the selected designs were then simulated at the operating points of the driving cycle. The optimal design from each optimization was chosen from the Pareto front of the optimization results, which corresponds to the optimization objective and constraint, efficiency, and torque ripple, respectively. The stator and rotor laminations of the selected design from the optimization using the X-Means are shown in Fig. 17(a). The magnetic flux density map at the rated operating point is shown in Fig. 17(b).

The average efficiency η_{avg} and the driving cycle efficiency η_{cyc} are calculated as shown in the following equation:

$$\eta_{\mathrm{avg}} = \frac{\sum_{i=1}^{N} \eta_i}{N} \tag{17}$$

$$\eta_{\mathrm{cyc}} = \frac{\sum_{i=1}^{N} \eta_i \cdot P_i}{\sum_{i=1}^{N} P_i} \tag{18}$$

where N is the number of operating points and η_i and P_i are the efficiency and power of the selected design at the operating point i, respectively.

As shown in Table VII and Fig. 18, increasing the number of RPs considered in the optimization improves the efficiency

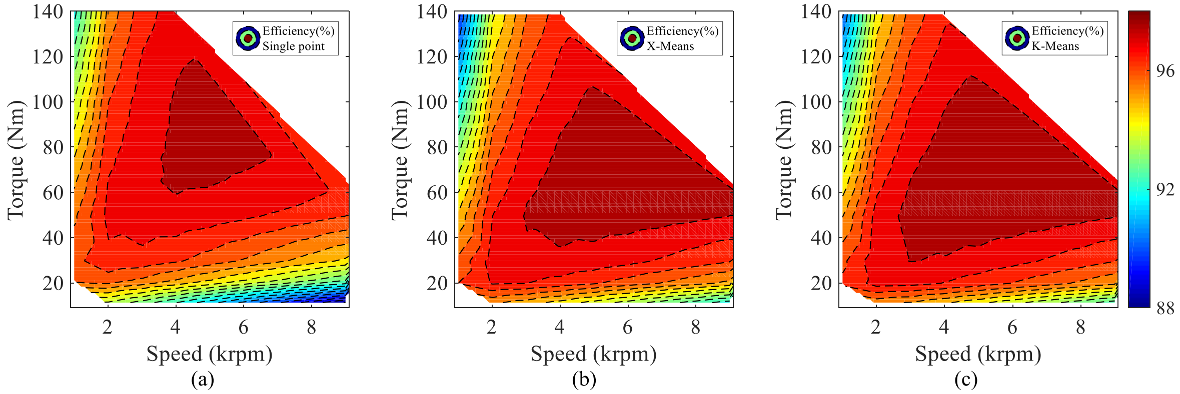

Fig. 19. Efficiency maps of the designs selected from the optimizations using (a) single point, (b) X-Means, and (c) K-Means.

TABLE VII
COMPARISON OF OPTIMIZATION RESULTS

Optimization	A	B	C
Number of RPs	1	2 (X-Means)	7 (K-Means)
η_{avg} (%)	95.27	96.24	96.43
η_{cyc} (%)	95.64	96.51	96.65
Maximum efficiency (%)	97.55	97.76	97.87
Normalized computational time	0.11	0.25	1.00

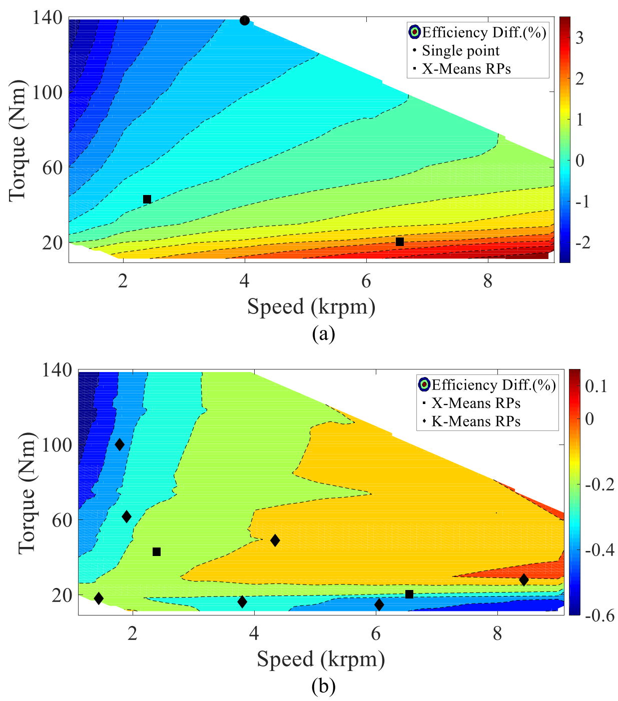

Fig. 20. Efficiency difference and location of RPs. (a) X-Means–single point. (b) X-Means–K-Means.

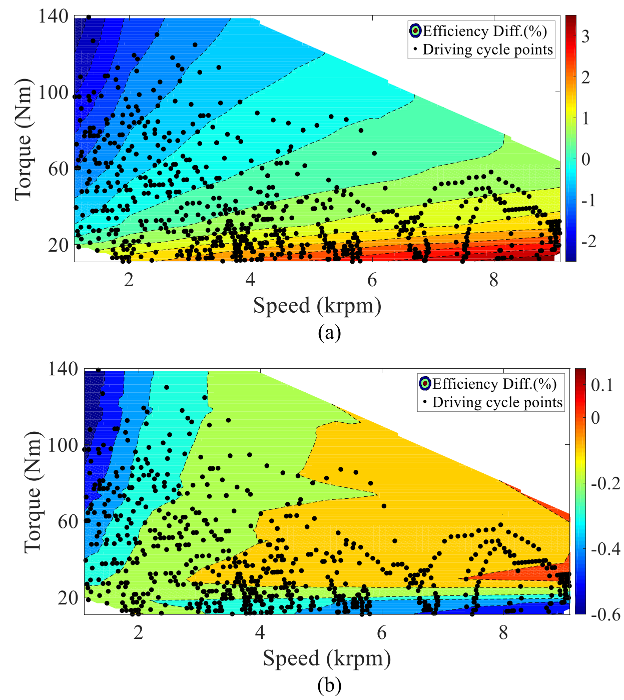

Fig. 21. Efficiency difference and driving cycle points. (a) X-Means–single point. (b) X-Means–K-Means.

across the driving cycle. However, the computational cost, which corresponds to the time needed for the optimization, increases considerably as well. Considering the operating points of the driving cycle (X-Means and K-Means) resulted in an improved cycle efficiency compared to the case where the machine geometry is optimized for the rated operating point (single point), without taking into account the driving cycle operating points. The efficiency maps for the three optimizations are shown in Fig. 19 to demonstrate the effect of increasing the number of RPs on motor efficiency. Fig. 19 clearly shows that the improvement in efficiency starts to decline with the increasing number of RPs. Therefore, the X-Means can provide an appropriate number of clusters and RPs to improve the driving cycle efficiency with reduced computational cost compared to the K-Means.

Fig. 20 shows the efficiency of the X-Means, relative to the cases of the single point and K-Means. Fig. 20 (a) and (b) demonstrate the effect of the location of the RP on the efficiency map. For example, the single point case showed better efficiency only near the knee point (high torque and below base speed region) due to the location of the RP used in optimization. The difference in the calculated values of the average and weighted for the three cases can be clarified in Fig. 21, where the distribution of the driving cycle points on the torque–speed plane is shown. In Fig. 21(a), more points are located in the regions of higher efficiency, which results in an enhanced average efficiency value. This demonstrates the expected effect of clustering in biasing the optimization to improve the efficiency at regions with high densities of operating points. Furthermore, the efficiency difference between the X-Means and K-Means cases does not exceed 0.2% for more than half of the plane, which demonstrates the ability of the X-Means to find a fair tradeoff between accuracy and computational cost.

V. Conclusion

This article discusses the fundamentals of data clustering methods toward driving cycle analysis to identify clusters, RPs, and optimization weights. It presents a comparative evaluation of the pros and cons of multiple data-clustering methods in the context of machine design optimization. An X-Means approach has been introduced to identify clusters and RPs in the torque–speed profile. This method offers a systematic approach as compared to visual inspection, arbitrary range split, and energy distribution methods and is able to determine an optimum number of RPs compared to the K-Means algorithm. In order to evaluate the significance of the number of RPs in the machine design optimization and the effectiveness of the proposed method, a case study has been carried out using the WLTP driving cycle.

This study shows that considering the operating points of the driving cycle (X-Means and K-Means) results in an improved cycle efficiency compared to the case where the machine geometry is optimized for the rated operating point (single point), without taking into account the driving cycle operating points. Furthermore, one can conclude that increasing the number of RPs used in the optimization would not guarantee a proportional improvement in the efficiency of the design for a given driving cycle. This can be related to the fact that it is difficult for the optimization to find a single-motor geometry that guarantees a significant improvement for the entire operating range of the motor.

Based on the results from X-Means and K-Means optimizations, the number of RPs should be identified to maintain a tradeoff between driving cycle efficiency and computational cost. Finally, this article concludes that the X-Means algorithm can effectively be used to develop an automated algorithm for identifying the optimal number of RPs, which can lead to significant improvement in the average efficiency of the design with a minimal increase in computational cost. This approach also enhances reproducibility of the results independent of the designer's intervention, by defining a mathematical basis for identifying the RPs.

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