IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 17 July 2023, accepted 8 August 2023, date of publication 23 August 2023, date of current version 30 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3308029

RESEARCH ARTICLE

EIS-Based SoC Estimation: A Novel Measurement Method for Optimizing Accuracy and Measurement Time

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This work was supported in part by the Italian National Center for Sustainable Mobility (MOST), funded by the Italian Ministry of University and Research (MUR) in 2022–2025, in part by the ''Innovazione per il Controllo avanzato e la gestione di Grid Energetiche'' Project within the Puglia Fondo Europeo Sviluppo Regionale (FESR) 2014–2020 under Grant CUP B81B22000020007, and in part by the Power4Future S.p.A., funded by the Italian Ministry of Enterprises and Made in Italy (MISE) under Grant CDS000944.

ABSTRACT The paper proposes a new experimental measurement method for State of Charge (SoC) estimation able to optimize between measurement time and target Accuracy adoptable in Battery Management System (BMS) design where both these parameters are key parameters for the overall management performance. The method is applicable when the SoC is estimated in classes through Electrochemical Impedance Spectroscopy (EIS) and is based on two operating stages: i) the experimental characterization of the real behavior of the considered batteries, ii) a time–Accuracy optimization based on suitable feature selection and Machine Learning approaches. In detail, as for the ii) phase, fixed the number of classes in which the SoC is estimated, the proposed measurement method finds the minimum number of impedance spectrum frequency measurements useful for SoC estimation. This is a big issue for BMS designers since in SoC estimation performed by EIS the measurement time is typically greater than some minutes if no optimization is considered. A possible strategy to reduce the required time for SoC estimation could be using Feature Selection (FS) techniques. In our method the FS is implemented using different combinations of search algorithms and fitness functions. Since FS strongly depends on the experimental set–up, the uncertainty of the measurement system, and the classifier adopted for the data–driving evaluation model, the proposed method is flexible and customizable depending on the specific applications. For this reason, the method is divided into steps where the BMS designers define the requirements based on their needs and their hardware. Also the output FS could be adapted to the different exigencies because the selected features could be different if more emphasis is on increasing classification Accuracy or decreasing the measurement time. Hence, we suggest two application scenarios: in the first one, the only requirement is increasing the classification Accuracy rather than the measurement time optimization. The second scenario has both a classification Accuracy target and lowering the measurement time. We also noted that the proposed method is useful also for increasing the overall classification Accuracy because naturally excludes the features that deceive the classifiers. As an application for the proposed method, we developed an automatic measurement system and performed an experimental campaign on seven Lithium Iron Phosphate batteries. The experimental results show that the proposed approach, for all the considered combinations, significantly reduces the measurement time required for EIS while maintaining high SoC estimation Accuracy. Furthermore, for all the obtained solutions, the effectiveness of our approach was confirmed by the significant savings in measurement time. In particular, the best solution reduces from 4 minutes when using all features to about 1.5 seconds with the selected features.

The associate editor coordinating the review of this manuscript and approving it for publication was Alon Kuperman.

INDEX TERMS Batteries, state of charge estimation, electrochemical impedance spectroscopy, feature selection.

I. INTRODUCTION

The crucial task of a Battery Management System (BMS) is to provide security and longevity of the battery. This can be done through the accurate and continuous monitoring and control of the battery's State of Charge (SoC) and State of Health (SoH). The accurate and real time knowledge of these parameters, see [1] and [2], allows to accomplish for some crucial tasks as the estimation of the remaining life range, the battery cell balancing [3], the temperature monitoring and control, and so on. Currently, regarding the SoC estimation, the most used techniques are based on the Coulomb counting and the Open Circuit Voltage (OCV). The Coulomb counting is basically the current integration over time [4]; in this case, the measurement error and knowledge of the initial SoC are huge problems. Also, Lithium Iron Phosphate (LFP) batteries have a flat relationship between voltage and SoC, meaning that a small error in voltage measurement generates a large error in SoC estimation; this is the main disadvantage of the OCV–based method. Electrochemical impedance spectroscopy (EIS) could be a good candidate to replace Coulomb/OCV counting techniques in SoC estimation [5], [6]. In fact, it does not suffer from the problems just discussed and has the potential advantage of being able to be applied online, in the real operating conditions [7]. EIS techniques require generating a stimulus signal (usually sinusoids) and measuring the battery voltage and current. The stimulus signals frequencies are in the range between a few mHz to a few kHz [8], [9]. The main problem with EIS concerns precisely the big measurement time, related to the use of the lower frequencies of the stimulus signals. In fact, they greatly increase the measurement time by reducing the possibility of being able to estimate the SoC in real–time.

This paper tries to find a solution to this issue proposing a first measurement method able to minimize the measurement time given a target Accuracy in SoC estimation when an EIS approach and a knowledge–based on SoC classes are considered. Accordingly, the purpose of this paper is to provide methodologies for optimizing the EIS used for battery SoC estimation. Given the generality of the proposed approach, it is applicable in all contexts where the problem of designing a system for real–time SoC estimation using the EIS technique is addressed. In fact, depending on the requirements of different applications, such as the accuracy to be achieved and the measurement time required to perform SoC estimation, the proposed method allows optimizing the choice of frequencies to be used in the EIS to satisfy the constraints imposed. Potentially, considering the three parameters of interest in the SoC estimation such as the number of classes in which SoC is divided, the target Accuracy and the measurement time, the proposed method is able to optimize two of these parameters by fixing the third one. For example, having fixed the number of classes in which SoC is divided, the method allows maximizing the classification Accuracy without constraints on measurement time, or minimizing measurement time without constraints on the classification Accuracy, and finally optimizing in the sense of finding a trade–off between the classification Accuracy and measurement time when there are constraints on both due to specific applications. The method is based on two operating stages: i) the experimental characterization of the real behavior of the considered batteries, ii) the time–Accuracy optimization based on suitable feature selection and Machine Learning (ML) approaches. As for the ii) point some considerations can be addressed. Typically, in EIS, stimulus frequencies in the mHz to kHz range are used, and the number of frequencies is at the operator's discretion. The greater the number of frequencies, the better the spectrum knowledge but the longer the measurement time. The selection of the minimum number of measurements at the key frequencies is the crucial point of this optimization. Adopting a ML approach, we can assume that each measure, at a different frequency, can be considered as a feature of the algorithm. Then this problem can be solved with a feature selection (FS) approach. FS reduces the number of input variables when developing a predictive model. The benefits of FS include improved model performance, reduced overfitting, increased interpretability, and reduced computational complexity [10].

The approach based on FS was also proposes in [11] where the authors acquired a dataset of 54 frequencies on Li-ion batteries at five different temperatures. They then used a Pearson's Correlation Coefficient–based method to extract the frequencies most correlated with the SoC to use as input for a ML model and linear regression. In their approach, it is unclear which frequencies are selected and how much the selection impacts the reduction in measurement time. In addition, as better shown in the paper, correlation offers lower selection performance than other proposed fitness functions. Other applications of FS concern the health status of batteries. In [12], the authors performed FS from voltage temperature and current measurements to identify indicators most correlated with the health status of LFP batteries. The batteries are aged through 121 equivalent charge and discharge cycles. As features, the authors use the time the battery has to spend between two voltage thresholds, temperature, current, and energy measurements. In the end, 69 features were obtained. After Gray's relationship analysis, the features were sorted from least to most correlated to SoH. By defining a correlation threshold is possible selecting the most important features.

The measurement method proposed in the paper extends the our research activity presented in [13], aimed to minimize the time required to perform EIS through a feature selection technique based on Genetic Algorithms (GA). We have extended that research activity in several directions. To better validate our results, we augmented the experimental data by considering more batteries than those used in [13]. We have also investigated the effectiveness of the Particle Swarm Optimization algorithm [14] as a search strategy alternative to GA–based techniques [15]. Furthermore, we have implemented two fitness functions. The first was used to evaluate the performance achieved by training a supervised learning model (wrapper approach). In this case, we tested several ML models to choose the best–supervised learning model. On the other hand, the second fitness was based on a correlation analysis using Pearson's Correlation Coefficient. The experimental results demonstrated the effectiveness of the FS approach proposed; we achieved similar or even higher SoC estimation accuracies than using all available features (i.e., not making feature selection) but with significantly shorter measurement times. The selection of features with the highest Accuracy allowed a huge reduction of the measuring time, from 4 minutes with all features to 1.5 seconds with the selected features. Furthermore, FS it is also important to note that some features are misleading for the classification algorithms. Therefore, their elimination allowed for a gain in the SoC evaluation Accuracy. Indeed, with all features, the maximum Accuracy for the SVM classifier is 0.87, and the same classifier with the selected features has a maximum Accuracy of 0.98.

The innovative points of the paper are listed below.

- First, a FS–based experimental method was developed that can optimize EIS for real–time battery SoC estimation applications. The proposed method has a completely general validity and can be applied during the design of a battery SoC estimation system, regardless of the application context.
- Subsequently, in order to experimentally validate the proposed approach, an intensive experimental campaign was carried out on LFP batteries. This activity allowed the authors to obtain a dataset regarding the characterization of batteries at different stimulus frequencies and different SoCs. The authors' intention is to share the dataset with the scientific community in future publications.
- Finally, the proposed method achieves better SoC estimation performance than using all features, which significantly improves the measurement time.

This paper is organized as follows. Section III reports the experimental campaign describing the set–up and the measurement protocol used to create the dataset. Section IV describes the conducted preliminary tests to choose the best-supervised learning model to consider within one of the fitness functions. Section V explains in detail the implemented procedures to perform the Feature Selection. Finally, Section VI shows the obtained results, and Section VII provides the conclusions of the work.

II. THE PROPOSED METHOD

Adopting impedance spectroscopy as an SoC evaluation method in Battery Management Systems (BMS) allows systems to avoid the use of Coulomb counting or Open Circuit Voltage. The latter methods, by their nature, tend to diverge over time or be less reliable during battery charge or discharge phases. However, impedance spectroscopy has a major limitation represented by the time required to make a measurement. This is mainly due to the low inspection frequencies that result in measurement times on the order of minutes. Such long times may not be compatible with some applications. To reduce the measurement time without significantly compromising performance in SoC estimation, a data-driven methodology for SoC estimation is proposed. In detail, the proposed method addresses the problem of designing a system for real–time SoC estimation using the EIS technique. In fact, depending on the requirements of different applications, such as target Accuracy to be achieved and measurement time required to perform SoC estimation, the proposed method allows optimizing the choice of frequencies to be used in EIS in order to meet the target constraints imposed. In this method, optimal frequencies are selected using feature selection approaches based on search algorithms and different fitness functions.

The proposed method follows the scheme shown in Figure 1. The first step is to define the design parameters and constrains, listed below.

- Resolution of SoC output estimation: the higher the resolution the longer the characterization step and in general the greater the number of classes and the greater the classification error.
- Target measurement time: the target measurement time is the maximum acceptable time to obtain the measurement.
- Accuracy target: is the minimum acceptable Accuracy of the classifier for SoC estimation.
- The type of batteries: the characteristics of the batteries you want to use (chemistry, nominal capacity, nominal voltage etc.).
- Classifier: the proposed method uses a classifier built into the search algorithms to estimate the population. The choice of classifier is critical because the next

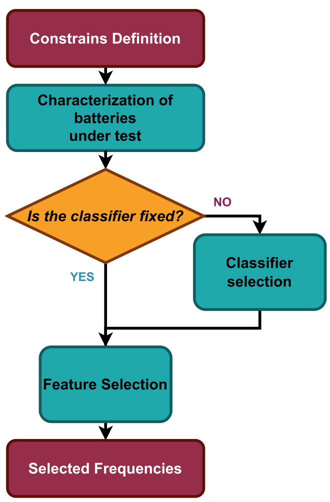


FIGURE 1. The proposed method workflow.

optimization step will be stitched around the classifier, in other words, the features selected also depend on the classifier adopted.

The classifier is sometimes defined by design parameters related to hardware requirements, while at other times the choice of the classifier is related solely to classification performance. The proposed method addresses both of these needs; the classifier can be an input parameter or a preliminary step will be used to identify the most suitable classifier for the dataset. The adopted classifier will constitute the data–driven method used by the BMS to estimate the SoC.

The second step is the characterization of the devices under test, in the characterization the tougher parameters possible are adopted, so the resolution in SoC must be the best possible, as well as the number of features measured. The batteries that make up the database must be chosen according to the future application of the BMS. Using different batteries of the same model allows generality to the different batteries, just as adopting batteries at different states of Health (SoH) allows the system to be proof to different SoH. If the classifier does not fit within the design constraints at this stage, the classifier best suited to the data set acquired in the previous Section is evaluated. The classifier that provides better Accuracy among a set of selected classifiers will then be integrated into the feature selection algorithm.

The last stage of the proposed method is feature selection where search algorithms can be used to select features with the dual goals of decreasing the measurement time to a value equal to and minor to the target time and at the same time having an Accuracy greater than the required target.

III. THE PROPOSED METHOD: CHARACTERIZATION OF BATTERIES UNDER TEST

This Section discusses the experimental approach used to obtain the dataset. An experimental campaign was conducted to evaluate the impedance of LFP batteries during their discharge. EIS technique was used to perform the impedance measurement while the reference SoC was estimated by the Coulomb counting method based on the integration of discharge current throughout the battery discharge process.

A. EXPERIMENTAL SET–UP

From the authors' experience in designing experimental systems [16], [17], Figure 2 shows the schematic diagram of the developed experimental set–up in order to experimentally characterize the impedance of LFP batteries as the SoC varies during the discharge process. In detail, the experimental set–up consists of the following components:

- a Hioki BT4560 battery impedance meter to measure battery impedance;
- a ZKEtech EBD–A20H electronic load used to discharge the battery with a controlled current;
- a climatic chamber based on Peltier modules to control and set the environmental temperature around the battery;

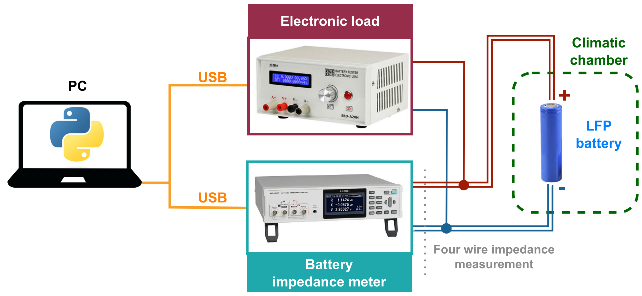


FIGURE 2. Implemented experimental set–up.

- a PC to manage the whole process by controlling the instruments via USB interfaces.

Finally, the impedance meter–battery and the electronic load–battery connections are made with the four–wire technique to reduce the impact of parasitic phenomena.

The implemented experimental set–up was used to characterize the behavior of 7 LFP batteries during their discharge process. The main characteristics of the considered batteries are summarized in Table 1.

TABLE 1. Main characteristics of the considered batteries.

Battery features	Values
Chemistry	Lithium Iron Phosphate (LFP)
Nominal capacity	600 mAh @ 0.2C Discharge
Nominal voltage	3.2 V
Minimum voltage	2.0 V
Charging voltage	3.65 V
Maximum continuous C-rate Discharge	2C
Maximum operating temperature	-10°C – 45°C (Charging) -20°C – 60°C (Discharging)

B. MEASUREMENT PROTOCOL

To characterize the behavior of the batteries through impedance measurement during their discharge process, a measurement protocol schematized in Figure 3 was implemented. This procedure was performed for all seven considered batteries. A detailed description of the measurement protocol is given below.

i) **Initialization**: initially, all the necessary conditions for performing battery characterization are set. These settings concern the characterization temperature, the relaxation time required for electrochemical recombination, the impedance measurement (the range and number of frequencies to be analyzed), the current used during battery discharge, and the SoC variation (ΔSoC) with which to perform the characterization. These conditions are summarized in Table 2 and detailed in the description of the measurement protocol.

ii) **Place the battery in the climatic chamber**: after reaching its thermal regime at a temperature of 20 °C, the battery is placed inside the climatic chamber.

iii) **Battery charging with CC–CV protocol**: at this stage, the battery is charged until it reaches the fully charged

TABLE 2. Adopted conditions for the experimental characterization.

Settings	Values
Characterization temperature	20 °C
Relaxation time	15 min
Frequency range	$[10mHz; 1kHz]$
Number of adopted frequencies within the considered frequency range	28
Discharge current	120 mA
ΔSoC	5%

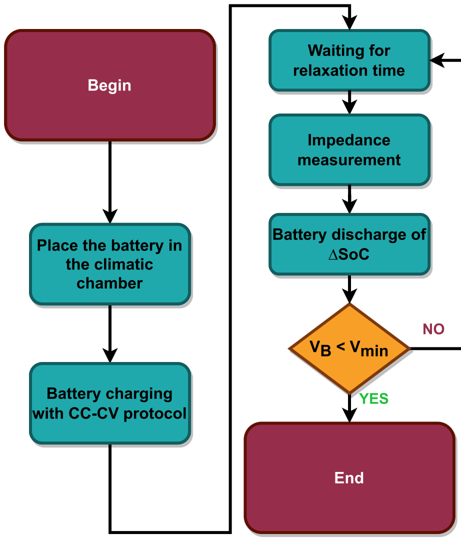


FIGURE 3. Adopted protocol for batteries characterization.

state (SoC = 100 %). This operation follows the standard Constant Current–Constant Voltage (CC–CV) protocol [18].

iv) **Waiting for the relaxation time**: to enable electrochemical recombination processes, it is important to add an interval between two consecutive discharge phases during the characterization phase. The relaxation time is the time required to reach equilibrium. The relaxation time is not unique but depends on the particular technology used. The adopted relaxation time for characterization was set to 15 minutes, as shown in Table 2. This result was achieved by performing several EIS experiments after discharging the battery and evaluating the measuring compatibility.

v) **Impedance measurement**: battery impedance measurement using EIS is performed with the settings shown in Table 2.

vi) **Battery discharge of ΔSoC**: the battery is discharged with a constant current of 120 mA until the SoC variation (ΔSoC) of 5 % is achieved.

vii) $\mathbf{V_B < V_{min}}$: here it is checked whether the battery voltage (V_B) has reached its minimum value (V_{min}). If not, the steps iv)–vii) are repeated; however, if the condition is met the battery is completely discharged. The minimum voltage value is provided by the manufacturer and is 2 V, as shown in Table 1.

viii) **End**: the characterization process is complete.

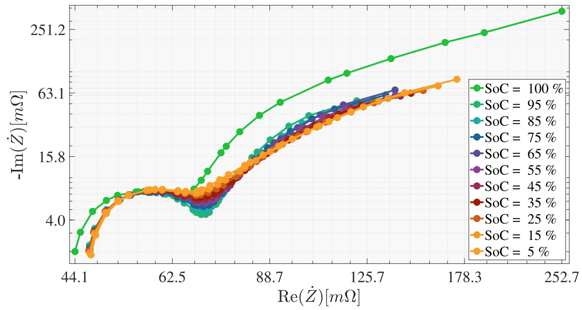


FIGURE 4. Obtained Nyquist plot of a single battery at different State of Charge.

As an example, Figure 4 shows the obtained result of the experimental characterization for a single battery. In particular, the Real and Imaginary parts of the EIS measurements obtained for all the analyzed SoC are shown. As can be seen from the figure, the measurement with SoC equal to 100 % has a very different behavior from the other measurements. This can be explained by analyzing what happens at an electrochemical level. With high values of SoC (close to 100 %), the concentration of lithium ions in the positive electrode (cathode) is small [19]. Since there are no lithium ions, the characteristic diffusion times tend to infinity, and the impedance is higher than the impedances of other SoCs.

Finally, Figure 5 shows the structure of the entire dataset obtained from our experimental campaign. For each battery tested, 20 SoC levels were considered, and 28 complex impedance measurements were obtained for each SoC level. Each impedance measurement comprises two real numbers (Real and Imaginary parts) to obtain 56 real features corresponding to a single SoC level.

IV. THE PROPOSED METHOD: CLASSIFIER SELECTION

As described in Section II the classifier could be defined from the project, but if it is not in this Section it showed how to select the best classifier for the acquired data. In this case to evaluate the data's validity and identify the best performing Machine Learning (ML) models for SoC estimation for the subsequent Feature Selection (FS) phase, preliminary tests were carried out in which all available features were considered. The performed experiments can be divided into two distinct steps. In the first phase, multiple ML models were analyzed to identify a subset of algorithms most representative of the problem under consideration, both in terms of achieved performance and computational complexity. In the second phase, the resulting models were used as the basis for in–depth analysis to evaluate their validity in real applications. The SoC estimation problem was represented through 10–class classification models, where each of the classes represents a 10 % SoC interval, thus producing estimation intervals $[0-10], (10-20], \dots, (90-100]$. As already mentioned, all available features were used, with 28 impedances for each SoC (Real and Imaginary part) acquired at different frequencies constituting the 56 features used. In addition,

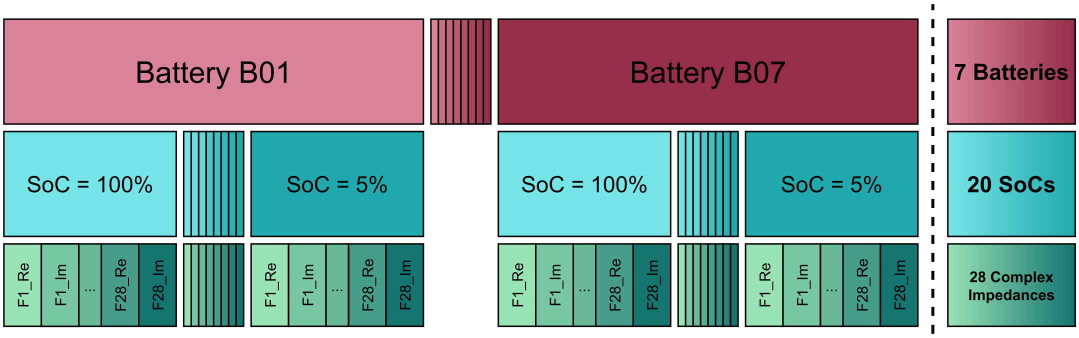


FIGURE 5. Structure of the entire obtained experimental dataset.

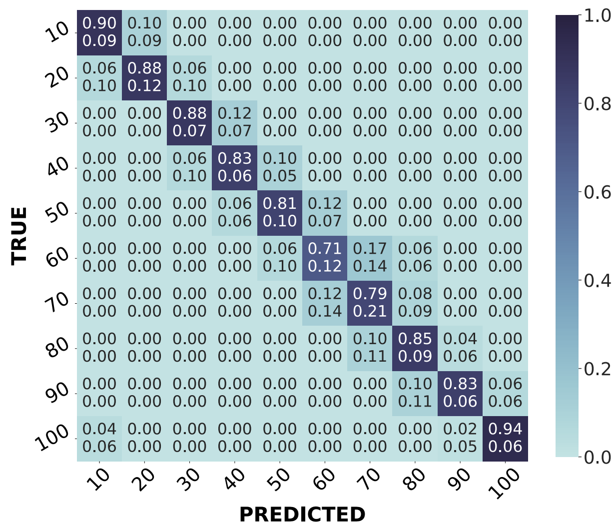


FIGURE 6. Obtained confusion matrix of the Support Vector Machine model, with mean value (top) and standard deviation (bottom) for each class.

no normalization techniques or more general pre-processing methods were applied, since standard techniques do not lead to significant improvements in the performance of the various models. In the various experiments, the principal metrics related to multiclass classification problems, as highlighted by Grandini et al. in [20], were used for performance evaluation. Accuracy (Acc), Matthews Correlation Coefficient (MCC), Precision (P), Recall (R), and F1 Score (F1) were used in this work. These are mainly defined for binary classification problems and were used in a multiclass context averaging the unweighted mean per label.

A. PRELIMINARY ANALYSIS

The dataset composed of seven LFP batteries was divided into two sub–datasets; the first one equal to 80 % of the data used to build the models (Training set) and the second one equal to 20 % of the data used to evaluate their performances (Test set). To properly analyze the various algorithms, it was also necessary to evaluate their response in relation to the variation of the respective hyperparameters. Consequently, the portion of the dataset used for training the models was further randomly divided into five folds, applying the k–fold cross–validation method. The analyzed models' related metrics and the best obtained hyperparameters are shown in Table 3.

From this analysis, three models were extracted to investigate their performance further. The chosen models are as follows:

- **K–Nearest Neighbors**, mainly characterized by negligible computational complexity for training and not very high performance.
- **Random Forest**, as a good performance/complexity trade-off.
- **Support Vector Machine**, to achieve the best performance.

B. IN-DEPTH ANALYSIS

The selected models in the previous phase were used to conduct further tests. In particular, the main purpose is to act in a controlled manner on the separation of data used for training and testing, thus ensuring that portions of measurements obtained from the batteries are not present in both Train and Test data. The experiments were conducted always following the k–fold method, using six folds in which measurements from two batteries were used as Tests and the remainder for Training. We then turned the batteries used in such a way as to make maximum use of the dataset, obtaining for each type of classification algorithm six trained models. The obtained results are shown in Table 4. The considered metrics confirm that the best performing model is the one based on the Support Vector Machine (SVM) with a mean accuracy of 0.83 and a standard deviation of 0.04. Figure 6 shows the resulting confusion matrix.

The final result of these preliminary classification tests allows the SVM to be identified as the best ML model among those considered. Hereafter, within the proposed FS methodologies involving the use of a classification model, the SVM will be the adopted model.

V. THE PROPOSED METHOD: FEATURE SELECTION

Feature Selection (FS) aims to decrease the number of used features by removing nonessential or noisy ones. Consider a set of data samples to be classified $\mathcal{Z}$, represented by a set Y

TABLE 3. Average values of the considered evaluation metrics and main best obtained hyperparameters for the ML models.

Model	Acc	MCC	P	R	F1	Hyper–parameter	Value
AdaBoost (DecisionTree)	0.34	0.31	0.32	0.36	0.27	Base estimator	Decision Tree
						Number of estimators	50
						Learning rate	0.1
Logistic Regression	0.45	0.39	0.43	0.45	0.43	Inverse of regularization strength	10000
						Norm of the penalty	l2
Multi–Layer Perceptron	0.55	0.52	0.52	0.57	0.51	Activation function	ReLu
						Hidden layer sizes	100, 200, 100
						Learning rate	Constant
						Solver	Adam
K–Nearest Neighbor	0.57	0.53	0.59	0.57	0.57	Number of neighbors	3
						Minkowski metrics	Euclidean
						Weight function	Distance
Gaussian Naive Bayes	0.68	0.65	0.72	0.68	0.67	Variance smoothing	1e-9
Bagging (DecisionTree)	0.75	0.72	0.77	0.74	0.74	Base estimator	Decision Tree
						Number of estimators	50
Random Forest	0.75	0.73	0.78	0.74	0.74	Criterion	log_loss
						Number of estimators	100
Support Vector Machine	0.89	0.88	0.92	0.89	0.89	Regularization parameter	10000
						Kernel type	RBF
						Kernel coefficient(gamma)	1
						Decision function	one-vs-one

TABLE 4. Average values and standard deviation of the considered evaluation metrics examined, where Train and Test datasets are divided by batteries.

	k-NN	Random Forest	Support Vector Machine
Acc	0.62 ± 0.12	0.79 ± 0.05	0.83 ± 0.04
MCC	0.58 ± 0.13	0.77 ± 0.05	0.82 ± 0.04
P	0.65 ± 0.11	0.81 ± 0.05	0.85 ± 0.04
R	0.63 ± 0.12	0.79 ± 0.05	0.84 ± 0.04
F1	0.62 ± 0.13	0.79 ± 0.05	0.84 ± 0.04

of N features. The FS problem involves finding the best subset $X^* \in Y$ of M ($M < N$) features using an objective function J. The function $J(X)$ evaluates the discriminatory power of the feature subspace represented by the subset X, when the samples in $\mathcal{Z}$ are projected onto it. Given an evaluation function, the optimal subset can be obtained by exhaustively evaluating all possible solutions. However, this exhaustive search is often impracticable due to the exponential increase in the number of solutions (2^N, where N is the number of available features). Therefore, many search techniques have been developed for FS to address this challenge, including complete search, greedy search, and heuristic search. However, since these algorithms do not effectively consider complex interactions among features, they often encounter problems such as being trapped in local optima or incurring high computational costs. Evolutionary Computation (EC) techniques have been widely used in this context as they are well known for their global search ability. Furthermore, EC techniques do not need domain knowledge and do not make any assumptions about the evaluation function, such for example linearity or differentiability.

In this work, we addressed the problem of identifying the optimal set of frequencies for impedance measurement by EIS for battery SoC estimation. To achieve this result, we used two optimization algorithms as search strategies; the former is based on the Genetic Algorithm (GA), and the latter is based on Particle Swarm Optimization (PSO). Furthermore, for both considered search algorithms, two different fitness functions are implemented: the first based on a supervised learning model and the second based on a correlation analysis. The proposed approaches in terms of search algorithms and implemented fitness functions will be described below.

A. SERCH ALGORITHMS

Figure 7 shows the schematic structure of both used search algorithms. Below both the GA and the PSO are discussed.

1) GENETIC ALGORITHM

A Genetic Algorithm (GA) simulate the natural process of evolution by creating a population of potential solutions, represented as binary strings, and modifying them using crossover and mutation operators to explore the search space [21]. The implemented method utilized a generational GA, where individuals were represented by binary vectors that encoded a subset of features. Each individual is a binary vector with a constant length equal to N, and where the feature inclusion or exclusion is coded respectively with 1 or 0. The algorithm flow chart is shown on the left side of Figure 7. To start the algorithm, a population of individuals P is created where each individual's values are randomly assigned as 1 or 0. Next, a fitness function is used to evaluate each

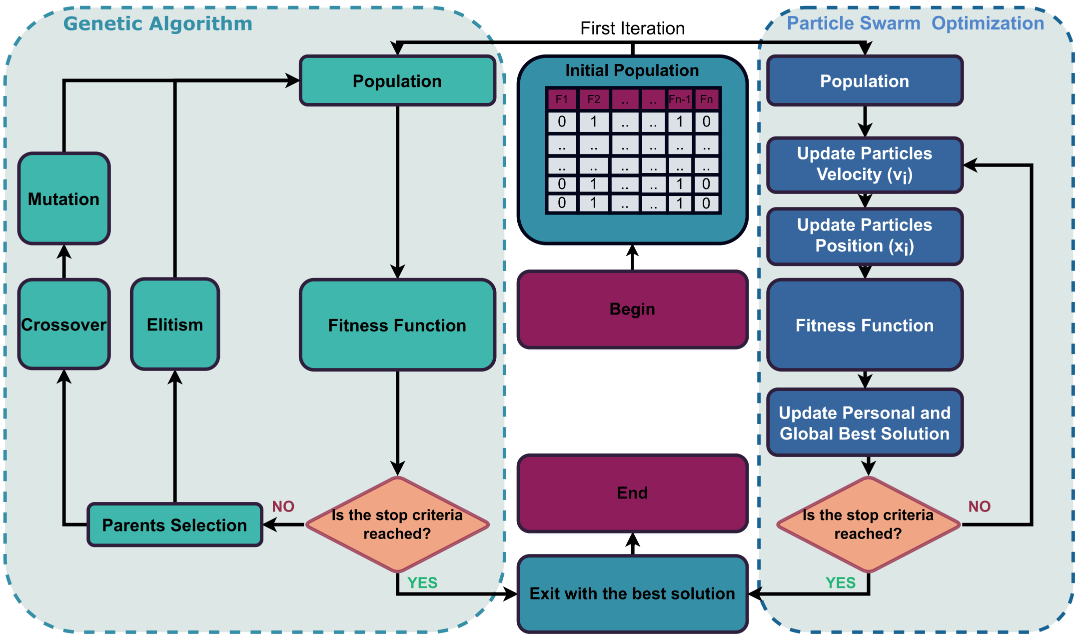


FIGURE 7. Genetic Algorithm (left) and Particle Swarm Optimization (right) flow charts.

individual's fitness, considering the set frequencies encoded by that individual.

Following this evaluation phase, a new population is generated by first implementing an elitist strategy that involves copying the best individuals from the current population to preserve the best elements in the current population. The remaining $(P - e)/2$ couples of individuals, referred to as parents, are selected using a tournament selection method of size t, where an individual from the population is chosen by selecting the best from t randomly selected individuals. The uniform crossover operator is applied to each selected couple, followed by the mutation operator, both of which are applied with probabilities equal to pc and pm, respectively. The resulting offspring are then evaluated and added to the new population. This process is repeated for Ng generations. All the setting parameter values of pc, pm, Ng are in Table 5.

TABLE 5. Genetic algorithm parameters.

Parameter	Symbol	Value
population size	P	100
selection type	-	tournament
tournament size	t	2
elitism	e	2
crossover probability	p_c	0.6
mutation type	-	random
mutation number of genes	m_{size}	1 bit
generation number	N_g	250

2) PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) algorithm [22] is a global optimization algorithm particularly well suited for solving problems in which the optimal solution is a point in a multidimensional space and can be used for both real-valued and discrete–data optimization. These swarm–based algorithms are a family of nature–inspired, population–based algorithms capable of producing robust solutions to various complex problems. A swarm consists of a population of simple, homogeneous agents that perform elementary tasks by interacting with each other and the environment.

From a mathematical point of view, as stated in (1), assuming that we want to solve a maximization problem and denote by f the objective function, the problem is defined as finding the $\boldsymbol{x}_{best}$ coordinate point, where the domain $\mathbb{R}^D$ is called the search space and the value of $f(\boldsymbol{x})$ is commonly referred as *fitness*. In PSO, each candidate solution $(\boldsymbol{x}_i)$ is called a particle and represents a point in the search space.

$$\begin{aligned} &f : \mathbb{R}^D \longrightarrow \mathbb{R} \\ &\boldsymbol{x}_{best} | f(\boldsymbol{x}_{best}) \geq f(\boldsymbol{x}) \qquad \forall \boldsymbol{x} \in \mathbb{R}^D \end{aligned} \tag{1}$$

The set of these elements constitutes the swarm, which in search of the solution to the problem, iteratively updates its position based on the equation of motion shown in (2), where v_i is a D–dimensional vector representing the components of the velocity of the $i - th$ particle, and the time instants t and $t+1$ represent two successive iterations of the algorithm [23]. From the algorithmic point of view, the iterative execution of the process is represented in Figure 7.

$$\boldsymbol{x}_i(t+1) = \boldsymbol{x}_i(t) + \boldsymbol{v}_i(t+1) \tag{2}$$

For solving the problem under consideration, the optimization algorithm was applied to discrete data [24], where each particle is represented by a binary vector that describes a subset of features. Table 6 shows the parameters used in the following experiments.

TABLE 6. Particle swarm optimization parameters.

Parameter	Symbol	Value
optimizer	-	Binary PSO
cognitive parameter	c1	2
social parameter	c2	2
inertia parameter	w	0.8
iterations	i	250
number of particles	n	100

B. FITNESS FUNCTIONS

As discussed above, two fitness functions were implemented for each considered serch algorithm. Fitness functions allow the selection of which features (and thus which frequencies) to use for SoC estimation. The idea behind the definition of both fitnesses is to consider two aspects: maximizing the information content of features and minimizing the overall measurement time. The measurement time is calculated as the sum of all selected stimulus periods. Since the measured impedances are complex numbers, that is, composed of a real and an imaginary part, two features are generated for each stimulus frequency. The instrument used for impedance measurement cannot measure only one of the two impedance components but outputs them simultaneously every time. For this reason, the measurement time is computed by counting a measurement period in case one or both the features at the same frequency are considered.

1) CLASSIFICATION-BASED FITNESS

We developed and tested a fitness function based on a *SVM* classifier because, as explained in Section IV, it is the most performative algorithm for classifying the State of Charge over the acquired data. The structure of the fitness function is shown in (3). The SVM is a supervised classifier that divides a projected space of features with hyperplanes. The optimal hyperplane is selected based on its ability to divide different classes on the test dataset. In the case of FS, the feature space changes at each iteration; let Ch be one of the Chromosome containing M features, our algorithm uses the M *dimensional* space on the training sub–dataset for selecting the best hyperplane. After the test is performed on the test sub–dataset with the same M *dimensional* space, the resulting SoC estimation accuracy is evaluated as shown in (4), where the A parameter is the fraction between the correct predictions CP over the total predictions TP. The focus of the FS in this application is reducing the measurement time, but in the meantime, saving the SoC estimation accuracy, or at least finding a good compromise. For this purpose, the measurement time is considered with the B parameter reported in (5). It has an inverse relationship with the duration of the measurement process, the term T_{meas} is the measurement time, and it is computed as the summation of the durations of the selected features (frequencies). On the other hand, the maximum measurement time T_{max} is determined by summing the durations of all features. In our case T_{max} is around 4 minutes. The use of measurement periods, instead of the number of features, enables the algorithm not only to minimize the number of features but also prioritize higher frequencies over lower frequencies because the impact of lower frequencies on the measurement time is higher than the impact of higher frequencies. Furthermore, the terms A and B lie within the range of [0, 1], while the α weight coefficient is a weight between the SoC estimation accuracy and measurement time contributions.

$$S = \alpha \cdot A + (1 - \alpha) \cdot B \tag{3}$$

$$A = \frac{CP}{TP} \tag{4}$$

$$B = 1 - \frac{T_{meas}}{T_{max}} \tag{5}$$

2) CORRELATION–BASED FITNESS

The fitness function based on Pearson's Correlation Coefficient (PCC), defined in (6) for a paired data $\{(x_1, y_1), \ldots, (x_n, y_n)\}$, aims to allow the identification of a subset of features such that the redundancy of information in the dataset is minimized. For each solution the algorithms return, the correlation matrix between the selected features is calculated, from which an index associated with the individual is obtained through the arithmetic mean of the unique elements in the matrix. Measurement time is also taken into account in the resulting optimization problem. The obtained function is structured as a maximization problem (7) and comprises two elements weighted using an α weight coefficient. The first element C shown in (8) is the term that represents the correlation index of the solution under consideration, while the second element B is inversely proportional to the measurement time as discussed above (5).

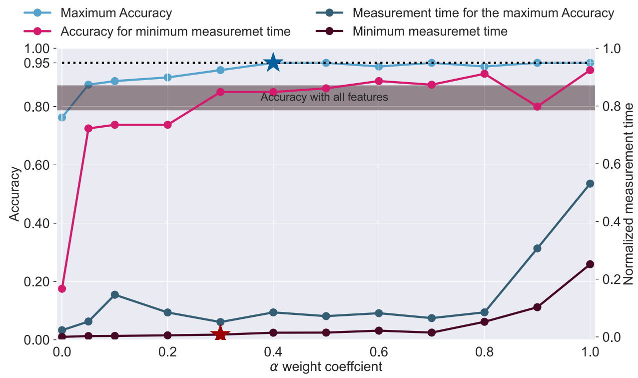
$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{6}$$

$$S = \alpha \cdot C + (1 - \alpha) \cdot B \tag{7}$$

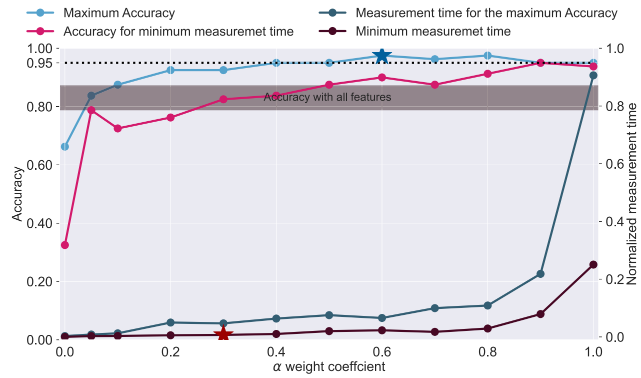
$$C = 1 - \frac{1}{n}\sum_{i=1}^{n}\left|r_{xy}(i)\right| \tag{8}$$

VI. PERFORMANCE EVALUATION

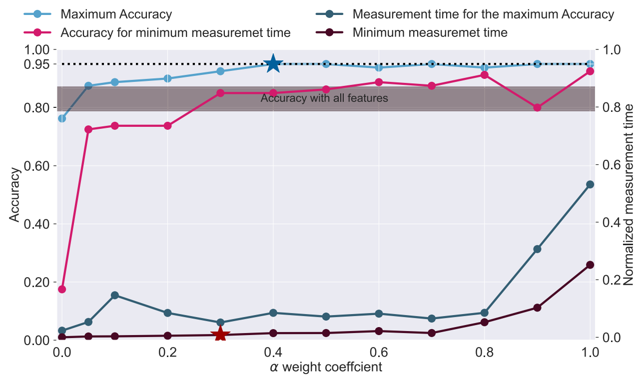
In this Section, we will discuss the results of the FS by applying the search algorithms and the fitness functions just discussed to the experimental dataset described in Section III. Specifically, we implemented the two fitness functions based on SVM and PCC on the GA and PSO search algorithms, obtaining four possible combination schemes: GA+SVM, PSO+SVM, GA+PCC, and PSO+PCC. The experimental parameters used for the GA and PSO in all experiments described in the following were set after some preliminary trials (see Table 5 and Table 6). Furthermore, to evaluate the performance of the tested systems, we performed 50 independent runs, each with a different initial population, randomly generated. At the end of each run, the best individual found was selected as the output solution for that run. The results reported in the following were computed by taking the best result in terms of Accuracy over the 50 runs performed. The hyperparameters used for SVM are the same as those



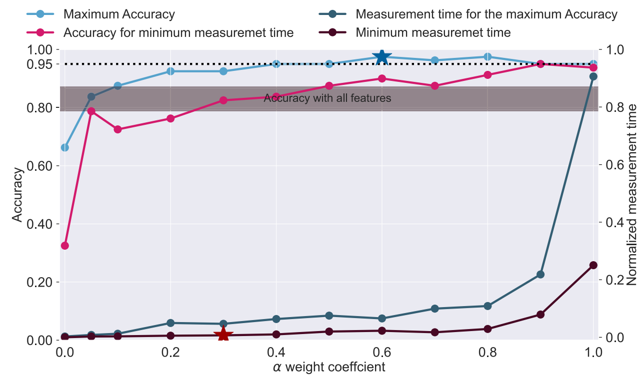
(a) Accuracy and measurement time as a function of α weight coefficient for GA+SVM combination.



(b) Accuracy and measurement time as a function of α weight coefficient for PSO+SVM combination.



(c) Accuracy and measurement time as a function of α weight coefficient for GA+PCC combination.



(d) Accuracy and measurement time as a function of α weight coefficient for PSO+PCC combination.

FIGURE 8. **Analysis of accuracy and measurement time as a function of alpha weighting coefficient for different configurations of search algorithms and fitness functions.**

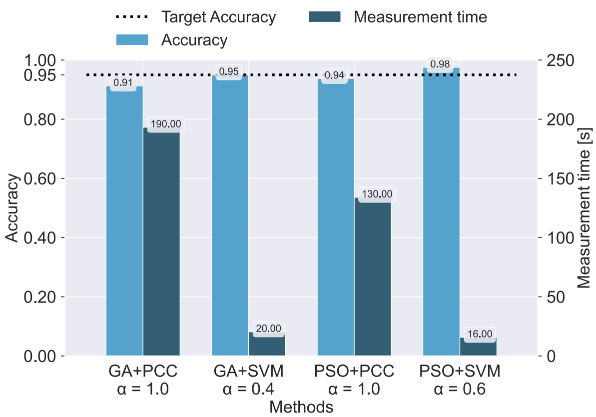
shown in Table 3. For each of the runs, the model construction follows the structure described in section IV-B, randomly selecting one of the available folds. Finally, the obtained performances were evaluated by considering several α weight coefficients within the implemented fitness functions (3), (7).

We imaged two different application scenarios, in the first one the goal is to select all the solutions with a classification Accuracy better than a target whatever the time. The second scenario instead, has multiple goals, select the solution with the minimum measurement time but without classification performance degradation with respect to the case with all the features. With this purpose, Figure 8 show the trends of the maximum Accuracy and measurement time obtained for each value of α, considering all combinations of fitness functions and search algorithms.

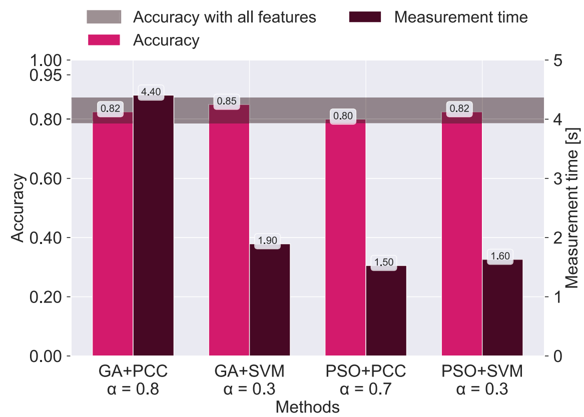
A. CASE STUDY A: ACCURACY TARGET

In this applied case study, we set a target Accuracy of 0.95 without taking into account the measurement time, the threshold should be defined into the requirements in Section II. Figure 8 reports the maximum Accuracy obtained through the 50 runs with its related measurement time as a function of the α weight coefficient. The dot marked with a blue star indicates the solution where the Accuracy is maximum. Lastly, the band represents the SoC estimation Accuracy obtained considering all features with the SVM classifier, along with the relative uncertainty, as reported in Table 4. For Accuracy, the higher is the value and the better is the solution, instead for measurement time is the opposite, lower is the value, and better is the solution. Regardless of the combination of fitness function and search algorithms, Accuracy increases as alpha increases. This phenomenon occurs because, with low values of alpha, search algorithms tend to generate solutions that minimize measurement time rather than maximize classifier accuracy. Conversely, high alpha values lead the search algorithms to place greater emphasis on Accuracy at the expense of minimizing measurement time. To assess the comparative solution searching performances of GA and PSO, not notable disparities between the obtained solutions' Accuracy can be observed in Figures 8a and 8b, this suggests that their performances are comparable. This observation holds true when comparing the solutions' Accuracy depicted in Figures 8c and 8d.

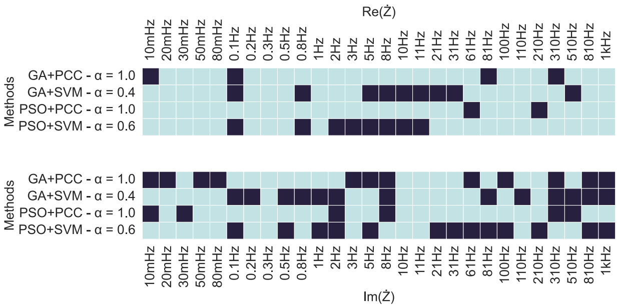
Regarding the fitness functions, it is clear that the one based on the SVM classifier achieves on average superior performance than the PCC algorithm in terms of Accuracy. In fact, the target Accuracy is reached only when the fitness function includes the SVM classifier. An interesting result is that the feature selection helps even to improve SoC evalua-



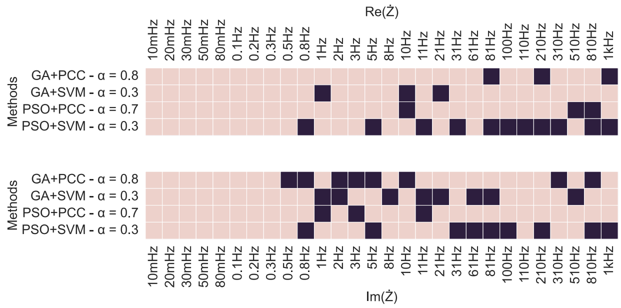
(a) Accuracy and time performances of the solutions with the higher SoC classification Accuracy.



(b) Accuracy and time performances of the solutions with two constraints on time and Accuracy.



(c) Distribution of selected features through the different combinations of searching algorithms and fitness functions for the scenario A.



(d) Distribution of selected features through the different combinations of searching algorithms and fitness functions for scenario B.

FIGURE 9. Performance analysis and distribution of selected features using different combinations of search algorithms and fitness functions for SoC estimation in the two scenarios A and B, taking into account the constraints imposed.

tion performances, there are several cases where the Accuracy is better than the one reached with all features. This fact could be explained by considering the presence of ambiguous features that trick the classification algorithm. Thus, even if there is no necessity of lowering the measurement time this method could exclude the bad feature and increase the overall classification Accuracy.

Figure 9a expand the star-marked points from Figures 8a–8d; the left axis reports the Accuracy while the right axis the measurement time for all the combinations of searching algorithms and fitness functions. From this it's clear that the better combination, for the acquired dataset, is the PSO+SVM for both the accuracy that reach 0.98 and the measurement time of 16 seconds. In this case, even if the optimization in time was not taken into account, the time saved is over 93% considering a total measuring time of 240 seconds.

Figure 9c shows the selected features for the real part and imaginary part of the impedance for all the stimulus frequencies. Comparing the real and imaginary parts is clear that for all the combinations the imaginary part looks more important for the classifier than the real part, because it is selected more times. Furthermore, the PCC tends to select fewer features than the SVM but more on the lower frequencies that have a higher impact on the measurement time.

B. CASE STUDY B: ACCURACY TARGET AND MINIMUM MEASUREMENT TIME

In this case study, we have established two constraints: one pertaining to the evaluation SoC Accuracy and the other concerning the measurement time. Specifically, our objective is to identify solutions that do not exhibit a degradation in Accuracy performance compared to the classification Accuracy achieved using all features outlined in Section II, minimizing the measurement time. Figures 8a–8d present the trends of the minimum measurement time for various values of the α weight coefficient, along with their associated Accuracies. The red star denotes the solution that exhibits the minimum measurement time while maintaining the Accuracy performances of the tests with all features. The measurement time increases as α approaches 1 due to the multiplication of the variable B in (3) and (7) with a coefficient $(1-\alpha)$ close to 0. It is worth noting that the Accuracy related to SVM classification displays a significant increase a α transitions from 0 to 0.05, followed by a gradual incline beyond $\alpha = 0.05$.

Figure 9b illustrates the solutions for minimum measurement time that also satisfy the Accuracy requirement. The lower measurement time is achieved using the PSO search algorithm with the fitness function based on the PCC. For all the selected frequencies, the system requires only 1.5 seconds, which accounts for less than 1 % of the measurement time when utilizing all features. A more detailed depiction of the selected feature for the second scenario is presented in Figure 9d. Due to the time constraint, all combinations of search algorithms and fitness functions tend to exclude lower frequencies, as they have a more substantial impact on the measurement time.

VII. CONCLUSION

In this work, we propose a measurement method to minimize measurement time in SoC estimation given the target Accuracy needed for the classification. It is based on selecting the most useful feature for a data–driven State of Charge (SoC) estimation. The aim is given to the Battery Management System (BMS) designers a workflow for optimizing the SoC estimation through a data–driven approach, instead simply presenting a result on a specific dataset. We think that is a winning approach because Feature Selection (FS) operation strongly depends on the acquired data, the chosen classifier, and other parameters.

The proposed FS is based on multidimensional search algorithms, specifically the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for selecting the most relevant features in the Electrochemical Impedance Spectroscopy (EIS) signals. Two different fitness functions are considered, one based on a supervised learning model, specifically Support Vector Machine (SVM), and the other based on feature correlation through Pearson's Correlation Coefficient (PCC). As a data source for the FS algorithms, we acquired an experimental EIS-based dataset consisting of seven Lithium Iron Phosphate batteries.

TABLE 7. Comparison of the analyzed scenarios based on some application examples. The first scenario (A) emphasizes accuracy, neglecting measurement time, while the second (B) achieves a use–case–dependent trade–off.

Scenarios	Target	Accuracy	Measurement Time [s]
A	Accuracy	0.98	16
B	Accuracy and Measurement Time	0.80	1.5

To create a reference by selecting all available features, the obtained classification Accuracy was 0.82 with a corresponding measurement time of 240 s. To show the potential of the proposed method, we explore two distinct application scenarios. In Table 7 the obtained results are reported for both scenario. In scenario A, the primary requirement is achieving a SoC classification Accuracy of 0.95, without taking into account the measurement time. The optimal solution achieves a classification Accuracy of 0.98, with a measurement time of 16 seconds, which is lower than the measurement time for all the stimulus frequencies. On the other hand, scenario B introduces two constraints: one on the classification Accuracy and another on the measurement time. In this case, the best solution identified by the search algorithms attains an Accuracy of 0.82, with a remarkable measurement time of 1.5 seconds. This impressive time–saving of up to 99% highlights the efficiency gained by utilizing the selected features instead the all measured features. Furthermore, it is crucial to acknowledge the impact of misleading features on the classification algorithms. Eliminating that features improves the SoC estimation Accuracy over 10% and demonstrates the importance of FS in optimizing the SoC evaluation performance even if saving time is not a priority.

These findings highlight the significance of careful FS for efficient and reliable of SoC estimation performance. The proposed method aims to give the BMS designers a new instrument that includes a multi–optimization fitness function that allows them to choose the weight of each aspect and consequentially focus the feature selection more on reducing the measuring time, increasing the classification Accuracy, or optimizing the number of classes. A Further step could include the adoption of a regression approach inside the proposed method for feature selection in order to obtain a continuous SoC estimation.

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Open Access funding provided by 'Università degli Studi di Cassino e del Lazio Meridionale' within the CRUI CARE Agreement