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Adaptive prioritization of a situation-based power management for hybrid electric vehicles

Bedatri Moulik, Kausik Bhaumik
Department of Electrical and Electronics Engineering, ASET
Amity University
Amity Campus Sector 125, 201303 Noida, India
bmoulik@amity.edu

Nejra Beganovic
Faculty of Science, Department of Electronics Design
Mid-Sweden University
Holmgatan 10, 85170 Sundsvall, Sweden
nejra.beganovic@miun.se

Ahmed M. Ali
Automotive Engineering Department
Military Technical College
Kobry El-Kobba, 11511 Cairo, Egypt
ahmed.m.ali@mtc.edu.eg

Dirk Söffker
Faculty of Engineering, Chair of Dynamics and Control
University of Duisburg-Essen
Lotharstrasse 1-21, 47057 Duisburg, Germany
soeffker@uni-due.de

***Abstract*—Hybrid electric vehicles can provide better performance assuming the power is intelligently and adaptively managed among the multiple sources in real-time. Most of the available power management strategies are either non-optimal or are not real-time applicable. Only a few focus on multiple and conflicting challenges of optimization objectives. In this contribution a fuel cell-battery-supercapacitor EV is considered with optimized rule-based power management. An important aspect of the optimized rule-based controller concept is its ability to offer flexibility of changing the priority or weights between the objectives so as to obtain an improved battery life or a better fuel economy or a better drivability. The weights are a representative of different rule-sets which prioritize either or a combination of the objectives. A concept of adaptive prioritization is proposed which can limit/allow the usage of each of the HEV sources depending on the driver/situation requirements and assumed future priorities. The simulation results with two different drive cycles, indicate the switching between rule sets to give better results with reference to one or two objectives at the cost of the other and vice versa.**

Nomenclature	
SoC	State of Charge
SoH	State of Health
DoD	Depth of Discharge
σ	Severity
Ah	Ampere hour
E_{FC}	Energy equivalent of fuel consumption
P_{demand}	Power demand
P_{FC}	Power from fuel cell
P_{SC}	Power from/to supercapacitor
P_{bat}	Power from/to battery

I. Introduction

Power management strategies in hybrid EVs mostly focus on ensuring optimal power split between different sources to fulfill various objectives. These objectives can be minimization of fuel consumption and emissions [1]–[4], drivability and range extension [5], [6]. They can also aim prolonging the life of the battery. Prognostic information can be used in power management actions based on the battery status and assumed future user requirements/priorities [7]. Various prognostics methods have been used to capture the aging phenomena in batteries [8]–[11]. Some contributions have proposed a battery health conscious power management which aims to prolong the life of the battery. For example in [12], [13] and [14]. However, power management of hybrid /electric vehicles often involve multiple and conflicting objectives [15], [16] for example fuel consumption minimization of hybrid electric vehicles will be difficult to achieve without compromising on the battery life. Similarly, a better range can be provided by pure electric vehicles if battery life is sacrificed. In both [15] and [16], the effect of different situations and user preferences on the trade-off relationships between the different objectives is emphasized. A decision on priorities between objectives has to be made depending on assumed future conditions. Prediction on future conditions is based on past and present conditions with some assumptions of the future and has been considered in [17]–[19]. Multi-objective optimization with energy minimization of total cost and minimization of battery degradation has been considered in [20] where a pareto-front was obtained of optimal solutions for the two objectives. It was concluded that minimizing energy cost required high state of charge (SoC) at the beginning of the trips, which in turn caused more degradation. Similarly, minimizing degradation compromised with the energy cost. The conflicting solutions obtained were compared in terms of the trade-offs made between the objectives. This could be extended to real driving scenarios where the weightage on the two conflicting objectives can be changed depending on the present and future conditions. It could be combined with prognostic-based power management that adapts itself situatively. In our previous contributions, an online, sub-optimal power management strategy [21] for a fuel cell-battery-supercapacitor powertrain which can dynamically allocate power between its sources depending on the drive patterns of the human driver, was proposed. The optimal power split between the battery and supercapacitor was decided on two conflicting objectives: minimization of fuel consumption and final and initial SoC deviations. Battery aging was included as an objective in [22] where capacity loss was determined for unknown load profiles. In this contribution, using the concept of severity map, the effective value of Ampere-hour (Ah) is computed; a rule-based power management controller is developed with predefined rule-sets for computing the power split between the fuel cell, battery, and supercapacitor. The values of power split are offline-optimized for three objectives: minimization of fuel consumption, battery degradation, and power difference (drivability). Since the three objectives may not be simultaneously satisfied so a 3D pareto front is obtained with different weights assigned to the objectives. A novel approach here is to allow flexibility in shifting the weights depending on the user priorities and the future conditions.

II. Weighted Ah models and severity factor map

Battery degradation and lifetime can be estimated as a function of certain parameters like voltage, current, temperature, SoC, and SoH. These parameters are estimated based on various modeling techniques [7]. Out of these, weighted Ah-throughput models relate battery EoL to Ah-throughput as the actual amount of current being drawn/supplied to the battery. According to [7], the severity of current in/out of the battery depends primarily on the C-rate, temperature, and DoD. Based on the nominal/standard operating conditions (known C-rate, temperature, and DoD), the actual operating conditions can be considered to be deviated from the standard by a severity factor σ as

$$\sigma(DoD, T_{batt}) = \frac{Ah - throughput_{nominal}}{Ah - throughput_{actual}}, \tag{1}$$

where the $Ah - throughput_{actual}$ is given by

$$Ah - throughput_{actual} = \int_0^{EoL} |I(t)|\, dt, \tag{2}$$

with $I(t)$ denoting the battery current.

This severity factor has been mapped in [7] as a function of DoD and temperature. It is used to calculate $Ah - throughput_{effective}$ as given in

$$Ah - throughput_{effective} = \sum w_e \cdot n_e \cdot Ah_e, \tag{3}$$

where e denotes an event and w_e, the weight or severity associated with the event, n_e, the number of events, and Ah_e, the actual Ah-throughput associated with that event. According to [7], the battery is supposed to reach its EoL when the $Ah - throughput_{effective}$ is greater than the $Ah - throughput_{nominal}$.

III. Power management control with adaptive prioritization

In the presence of multiple energy sources, the role of power management controller is to optimally split the power between the sources/storage components to fulfil a certain objective. However, optimization in case of hybrid electric vehicle control is rarely a single objective problem. In this contribution a previously developed rule-based power management control concept [21] is modified to include rule-sets instead of a single rule base. The optimization is performed for minimization of fuel consumption, minimization of degradation with is represented by Ah-effective, and power difference between the demanded and supplied power, also known as drivability. The drivetrain is purely electric with fuel cell-battery-supercapacitor. Specifications are given in [21]. The role of the power management controller is to request the desired current signals from the DC/DC converters connected to the three sources. The objective function for optimization using Multi-objective genetic algorithm (MOGA) is specified as:

$$f_1(y,z) = min \int_{t_0}^{t_{end}} E_{FC}\, dt \tag{4}$$

$$f_2(y,z) = min \int_{t_0}^{t_{end}} Ah_{effective}\, dt \tag{5}$$

$$f_3(y,z) = min \int_{t_0}^{t_{end}} P_{diff}\, dt \tag{6}$$

where the objective function f is subjected to variation of power split variables y and z. Here, f is a function of power demand, initial Ah, power split ratio, and SoC of both battery and supercapcitor. The energy consumption of the fuel cell equivalent to the mass of hydrogen consumed is represented by E_{FC}. The difference between the supplied and demanded power is represented by P_{diff}. The duration of the drive cycle is t_0 to t_{end}. The total objective function is given as,

$$f(y,z) = \int_{t_0}^{t_{end}} x_1 f_1(y,z) + x_2 f_2(y,z) + x_3 f_3(y,z) dt, \tag{7}$$

subject to

$$V_{bus_{min}} < V_{bus} < V_{bus_{max}} \tag{8}$$

$$SoC_{batt_{min}} < SoC_{batt} < SoC_{batt_{max}} \tag{9}$$

$$SoC_{sc_{min}} < SoC_{sc} < SoC_{sc_{max}} \tag{10}$$

and

$$x_i^L < x_i < x_i^U \tag{11}$$

$$y_i^L(n) < y_i(n) < y_i^U(n) \tag{12}$$

$$z_i^L(n) < z_i(n) < z_i^U(n) \tag{13}$$

Here, the constraints that is the bus voltage V_{bus}, and the battery and supercapacitor SoCs namely SoC_{batt} and SoC_{sc} are held within limits and the weights between the objectives x_1, x_2, x_3 are varied within predefined boundaries. Along with x, the other two optimization variables y and z are also bounded and expressed as a function of n where, n represents the rule number. The range in which n may vary is 1 to 10. This concept is explained in Figure 1.

For a certain drive cycle, having a finite duration t_0 to t_{end}, representing a certain situation, a rule number is chosen. This corresponds to certain rule base which assigns a particular value to the power split variables y and z. It also defines the weights between the objectives. The rule may be designed to prioritize fuel consumption for instance over the other two objectives. Another drive cycle or pattern may lead to a different choice of x which may prioritize battery life extension. Similarly, a number of intermediate values of x may also be chosen which offer a compromise between both objectives, or prioritize a third objective- drivability. Thus, the rule base x will decide the weight between the objectives

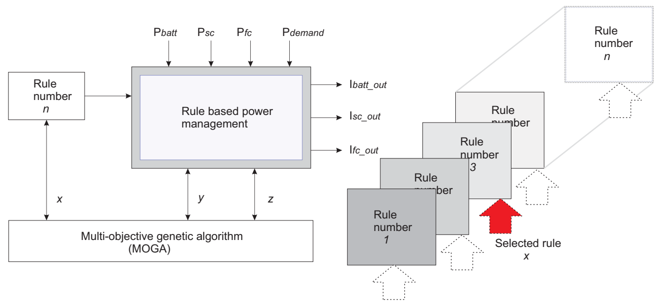

Fig. 1. Selection of optimal rule and powersplit

for a particular drive cycle. In this contribution, 10 rules are developed for both extreme and intermediate solutions. The logic of the rule-bases is explained in Figure 2.

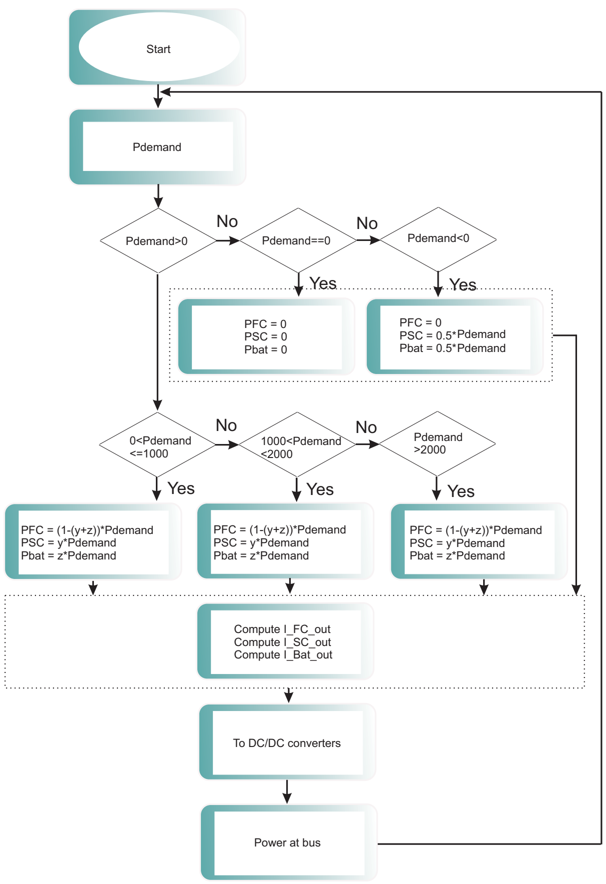

Fig. 2. Rule-based logic

The rule-based logic is explained in Figure 2. The power demand corresponding to a particular drive cycle is the input which may decide whether the vehicle is in accelerating ($P_{demand} > 0$), decelerating or braking modes. Here, PFC, PSC, and PBat represent the fuel cell, supercapacitor, and battery power output respectively. The values of power split may be chosen accordingly. For the $P_{demand} < 0$ case, the battery and supercapacitor are required to share the regenerated power equally. For the $P_{demand} > 0$ case, boundaries are chosen such that during low, medium, and high power demands, certain values of split (y and z) are chosen. During optimization, these split values are varied as a function of the rule number. In other words, depending on the rule number or the weightage given to each of the objectives, y and z will yield different cases. Ten such cases have been developed corresponding to ten rules. Finally, the desired current values I FC out, I SC out, I Bat out are computed considering the voltage to be constant. This desired current value is requested from the sources via the DC/DC converters.

In this contribution, two different drive cycles are used namely, FTP and WLTP, to predict the prioritization between the objectives. As a part of the future work, a combination of standard and real cycles will be used, together with a suitable drive pattern recognition algorithm to recognize unknown situations and user constraints. Based on the recognized drive cycle as shown in Figure 3, the rule-based power management controller will determine the most appropriate rule set. The corresponding power split values can be stored in a look-up table as obtained after optimization with respect to the three objectives. Thus the recognized situation or causes from outside will influence the weights between the objectives. The real-time applicability of the power management controller will be validated.

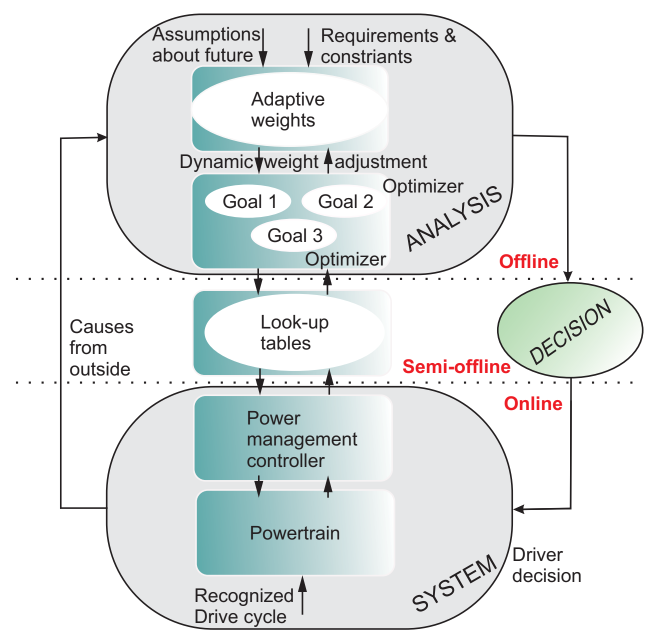

Fig. 3. Adaptive power management and dynamic weight adjustment

IV. Results and Discussion

The simulations for two drive cycles, FTP and WLTP are normalized and co-ordinated to have same time points. The values of Ah effective, fuel consumption, power difference between demanded and supplied power, battery and super-capacitor SoCs are plotted for FTP and WLTP as shown in Figure 4 and 5 respectively. The values corresponding to the ten rules are represented in different colored curves as shown in the figures. It is noted from Figure 4 and 5, that for the WLTP cycle the blue line (corresponding to rule number 2) has highest values of Ah effective. This rule however gives the lowest value of fuel consumption. The red dashed line (corresponding to rule number 8) has exactly the opposite effect. Apart from these two extreme rules, most of the other rules provide intermediate solutions. The power difference or drivability objective also attains slightly different values for the ten rules. With a different drive cycle, that is, FTP,

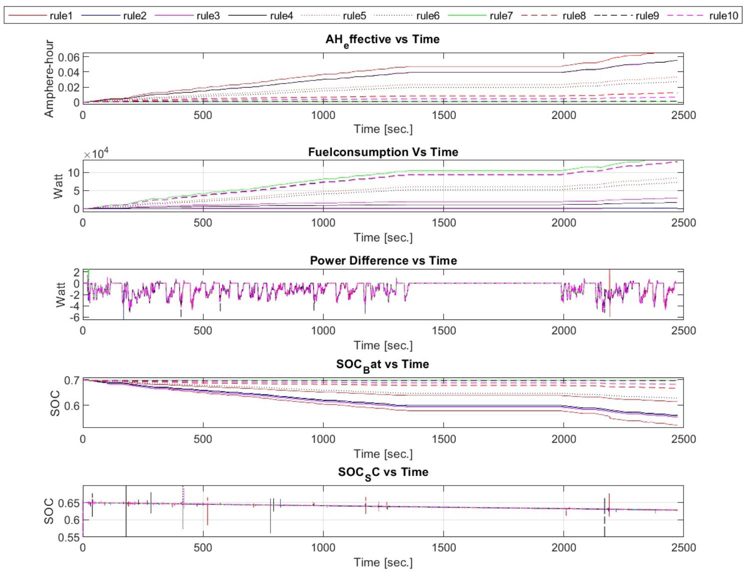

Fig. 4. Variation of powertrain parameters with rules for FTP cycle

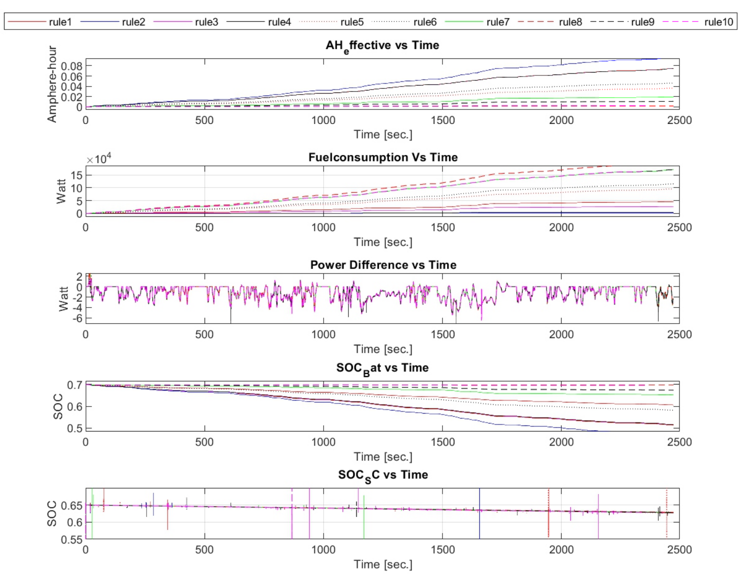

Fig. 5. Variation of powertrain parameters with rules for WLTP cycle

which represents quite similar driving conditions, a slight change in the rule numbers is observed in the sense that, rule number 1 corresponds to maximum Ah effective and rule 7 corresponds to maximum fuel consumption. In other words, under a certain driving cycle, a certain objective may be met by a certain rule number and a completely different rule number under another driving cycle. Therefore, depending on the drive cycle, and the users preference of objectives, a certain specific rule number has to be chosen in a given time frame. The distinction between the rules and corresponding preference between objectives is more evident in the spider plots shown in Figure 6. For the FTP cycle, the best rule set for minimum fuel consumption is rule 1 whereas the best rule set for minimum Ah effective is rule 9. For WLTP cycle, it is rule 2 and rule 8 respectively. The effect of change in rule-sets on the third objective-power difference is minimal. This however will not always be the case. An intuitive design of rule-bases considering other driving cycles/conditions can be made which may sacrifice drivability to further prioritize the other two objectives. The optimization results are represented in the form of 2D and 3D pareto optimal fronts in Figures 7 and 8. Here, it can be observed that individual pareto fronts for each of the ten rules combine to give different trade-offs which can then be chosen depending on the user/situation preferences. For example, a perfect compromise solution can be observed to be represented by the violet diamond and the red dot corresponding to rules 4 and 6 in the 3D pareto front of Figure 8. Thus the novelty of the contribution lies in the adaptability in prioritizing the weights between the objectives for the two chosen drive cycles. This can be combined with drive pattern recognition to give a more situation-based solution. As shown in the results, prioritizing fuel consumption and sacrificing Ah effective has led to a selection of different set of results as compared to when the case is opposite. The drivability is not compromised although a provision of compromising it based on situation is left for future work.

V. Conclusion

The main objective of this contribution is to present an adaptive power management which is capable of shifting the priorities between its objectives depending on the user preferences/drive cycle requirements. The idea is to develop rules which assign different weightages to three objectives. The total objective function is a weighted sum of fuel consumption minimization, minimization of battery aging and power difference between demand and supply. The optimized variables are computed offline and can be embedded online as look-up tables. An extension of the developed concept for real-time application is proposed, where, a dynamic weight adjustment is possible. The simulation results compare and contrast the different rules for two drive cycles and present the available options for an intelligent controller to select the most appropriate rule for the upcoming situation. This latter part will be taken up as a part of future work.

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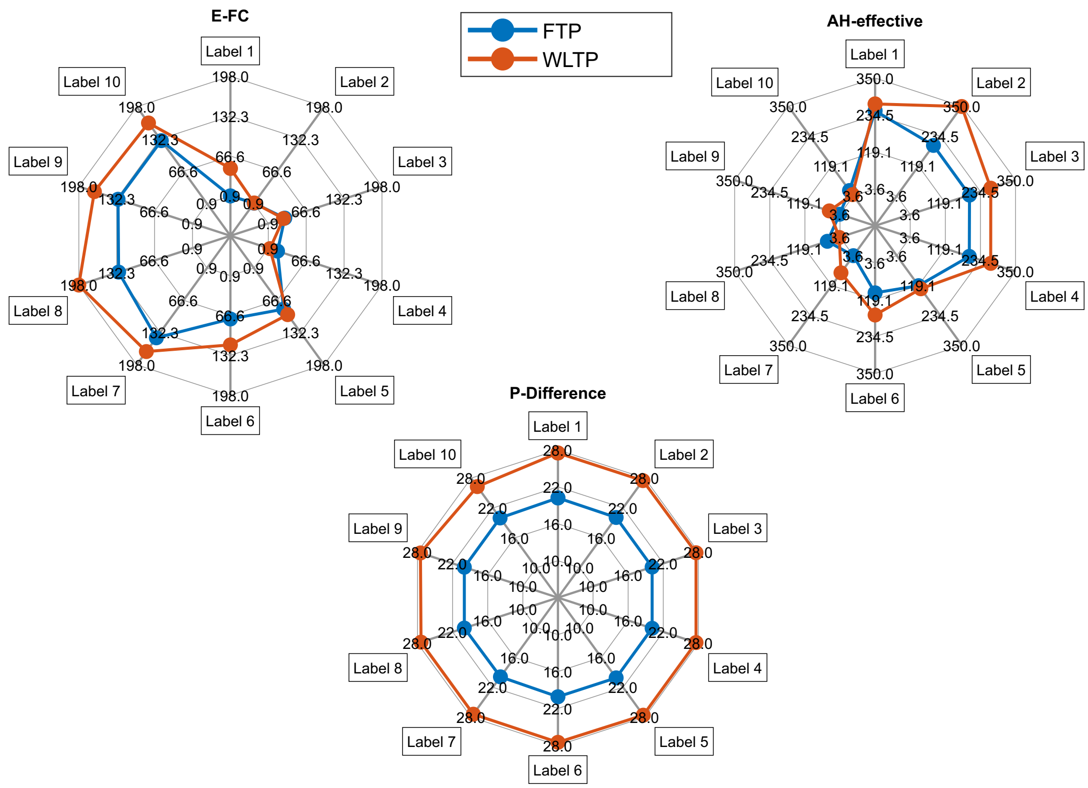

Fig. 6. Objective priorities for different rules

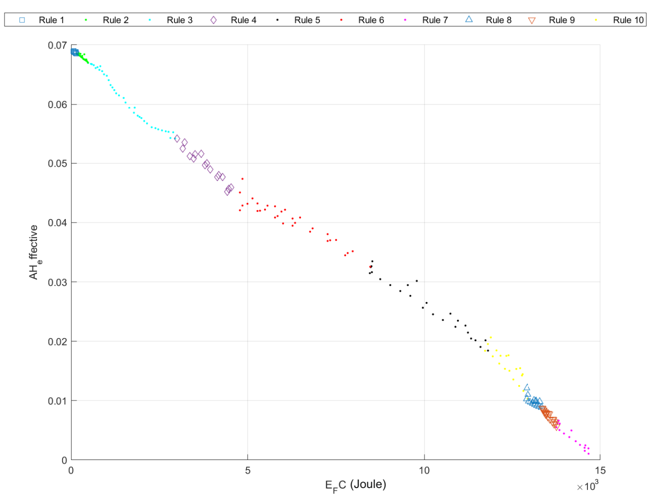

Fig. 7. Pareto-front for two conflicting objectives

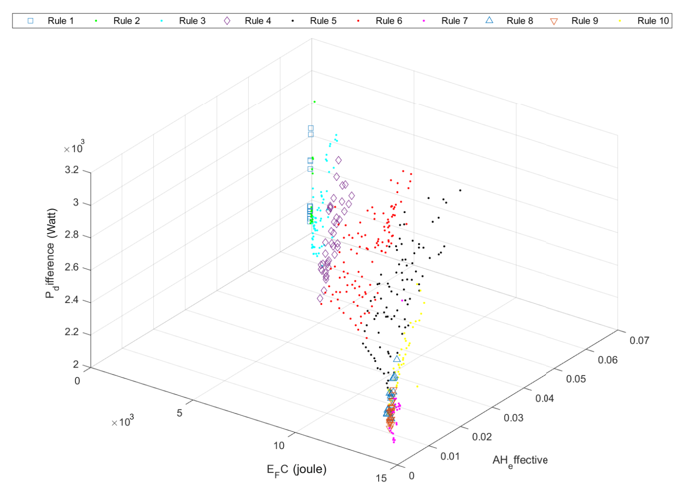

Fig. 8. A 3D pareto-front representation

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