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An intelligent energy management strategy for an off-road plug-in hybrid electric tractor based on farm operation recognition

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Abstract

Due to the growing emergence of vehicle electrification, agricultural tractor developers are launching hybrid powertrains in which energy management strategy (EMS) assumes a prominent role. This work mainly aims at developing an EMS for a plug-in hybrid electric tractor (PHET) to minimise fuel consumption and increase the operating range. The developed off-road PHET power sources are composed of a biogas-fuelled Internal Combustion Engine Generator (Bio-Gen), a photovoltaic system, and a battery pack. To control the power flow among different sources, a two-layer EMS is formulated. In this regard, initially, the farm operating mode is recognised by means of classification of a working cycle's features. Then, a control strategy based on a multi-mode fuzzy logic controller (MFLC) is employed to manage the power flow. At each sequence, the classifier identifies the farm operation condition and accordingly activates the relative mode of the MFLC to meet the requested power from the Bio-Gen. The performance of the proposed EMS has been evaluated based on three real-world typical agricultural working cycles. The results demonstrate the successful performance of the proposed intelligent EMS under farm conditions by maintaining the energy sources' operation in a high-efficiency zone which can lead to the extension of the working range and decrease fuel consumption.

1 | INTRODUCTION

Reducing environmental impacts and dependency on fossil fuels are considered important issues by energy policies around the world [1, 2]. Stricter environmental protection regulations, such as the European Stage V non-road emission standards [3], tighten the emission level in off-road vehicles, such as agricultural tractors and mining vehicles, which use internal combustion engines (ICEs) and have a significant share in the pollution [4]. Regarding the literature, powertrain electrification helps to increase overall vehicle efficiency and reduce exhausting emissions. Moreover, it can increase the controllability, reliability, and comfort in agricultural tractors [5]. In this regard, powertrain electrification seems to be a potential solution for the progress of the agriculture fourth revolution [5, 6]. One of the common technological solutions is to use pure electric vehicles. However, they suffer from long recharging time and low driving range limits. These limitations would be more drastic in off-road vehicles, which require more energy for travelling and doing some tasks in a short time [7]. In order to mitigate these shortcomings, several hybrid powertrains have been developed in the automotive industry [8]. Moreover, some research studies have been conducted in construction equipment and mining trucks' powertrain hybridisation. However, other kinds of off-road vehicles have not received enough attention [9, 10]. Among various hybrid electric configurations, a plug-in hybrid electric vehicle (PHEV) can be a suitable configuration for reducing fuel consumption because it can be charged by external electric power sources like renewable power plants [11]. Also, for a working range longer than the pure-electric working range, it is more economical to use a blended mode (ICE and battery together) than operating the vehicle as a battery electric vehicle [12, 13].

Regardless of the PHEVs flexible architecture, a proper energy management system (EMS) is necessary for online coordination between multiple energy sources. The EMSs of the HEVs are broadly classified into rule-based and optimisation-based methods [13, 14]. Rule-based methods, such as thermostatic control strategy (TCS) and fuzzy logic control (FLC), are easier to implement in online applications; however, they are less capable of finding optimal power management solutions [15]. Optimisation-based methods provide near-optimal solutions and can be combined with rule-based methods to revise the set of rules and inferential knowledge. They are subdivided into two categories: global, optimising the objective function over a known driving profile; and real-time, using an instantaneous objective function based on the variables of the system [16]. Optimisation-based EMSs in urban HEVs are mostly focussed on ensuring the optimal power split between different sources to meet different goals. These objectives can be the minimisation of fuel consumption [17], emissions [18], range extension [19], and drivability [20]. Literature consideration shows that, among variant EMSs, FLC is one of the most commonly used methods due to its flexibility, robustness, and convenient implementation [21]. [22]. FLC's performance could be improved by optimising its parameters for a specific driving cycle using an optimisation algorithm such as particle swarm optimisation (PSO) [23], model predictive control (MPC) [24], and genetic algorithm (GA) [25, 26]. Moreover, the use of the traffic condition and driving information in the design of an EMS, known as intelligent EMSs, can enhance the performance of an FLC-based strategy as discussed in [21, 27, 28]. However, in off-road applications, due to fluctuations in working conditions in terms of task variation and soil deflection etc., the use of speed profiles cannot solely be adequate. Additionally, these vehicles are usually used for doing some tasks, such as material handling, trailer pulling, lifting, which are completely different from what urban cars are made for. According to the reviewed literature, there were no specific standard working cycle or available model for the design and evaluation of electric off-road vehicles until now. Based on this knowledge, the fundamental problem for the powertrain electrification of an off-road vehicle is to study how work cycles affect the energy requirement which can help in the design of an EMS.

In this regard, the use of driving pattern recognition and prediction approaches for EMSs are introduced as efficient methods in [29, 30] for HEVs. Literature consideration shows that there are three main driving pattern prediction techniques including GPS-based technique, statistics and clustering analysis based methods, and the Markov chain-based technique. Among these methods, the statistics and clustering analysis based methods are preferable for taking full advantage of the on-board available data. The basic idea is to collect the historical and current driving cycle parameters to analyse the previous driving pattern and predict the driving conditions in the near future, typically 1∼2 min [31]. To recognise the current driving condition with the historical parameters, the characteristic parameters should be extracted from known driving cycles and be used in the classification tools or methods. The classification algorithms mainly include the Bayesian classifying algorithm, decision tree, rough set theory, fuzzy clustering analysis, neutral network, and the support vector machine [31]. For instance, methods based on fuzzy logic [32], neural networks [33], and other machine learning-based techniques [34] have been investigated to recognise current driving conditions and predict future driving conditions. For driving cycle recognition, the fuzzy clustering analysis and neutral network approaches are the most popular in on-road HEVs [35]. However, based on the author's knowledge, the working cycle pattern recognition problem in off-road HEVs' applications, such as agricultural tractors, have not been investigated in the literature.

Regarding the agricultural tractors' powertrain hybridisation as an off-road vehicle, different types of hybrid electric architectures including hybrid diesel electric and fuel cell electric tractors have been conceptually introduced by manufacturers and researchers [5]. For instance, a hybrid electric tractor is investigated in [36], but the EMS's design details are missing. Moreover, in terms of EMS for hybrid electric tractors, two simple EMSs, thermostat control strategy (TCS) and the power follower rule-based EMS, are utilised for a hybrid electric tractor through a simplified model in [37]. An extended-range solar assist plug-in hybrid electric tractor (ERSAPHT) is developed by employing a heuristic rule-based EMS by our team in [38]. The differences in agricultural vehicle applications, such as the working environment and expected duties, make the development of an off-road HEV powertrain more challenging compared to urban vehicles. For instance, tractors are usually designed in a way to pull diverse agricultural implements for repetitive off-road operations, such as transportation and fieldwork. An agricultural tractor needs a different range of torque and speed. For example, a high torque is required at a low speed for heavy tasks like ploughing, while partly high speed is desired for road transportation. In addition, the power take-off (PTO) system is typically used to transfer the power for driving the implemented machines by an agricultural tractor. In fact, tractor performance varies with respect to the implementation of different agricultural machinery with different levels of power requirements. Therefore, it could be beneficial to consider the different working patterns of the agricultural operation while designing a hybrid electric agricultural tractor.

To sum up, because of the lack of a systemic approach for designing off-road hybrid electric vehicles and their working conditions, it seems that there is a need to establish a holistic method. In this regard, the EMS problem in an off-road agricultural vehicle is investigated by using a simulation tool and some typical working cycles obtained from field experiments in this work. This work introduces an intelligent EMS for an agricultural hybrid electric tractor application. To do so, the working conditions of the off-road vehicle are recognised using the fuzzy C-means (FCM). Moreover, an optimised multi-model FLC is developed to perform energy management. The performance of the developed multi-mode FLC is compared with that of DP, which is an offline optimal strategy. In light of the discussed matters, the contributions of this work are as follows:

- Developing a working condition recognition tool for an off-road vehicle using some features, such as speed, acceleration, required power, and so on.
- Incorporating the working condition recognition into the design of an intelligent EMS based on the genetic fuzzy for an off-road vehicle.
- Employing measured experimental data from an ERSAPHT for validation purposes despite the existing studies in the literature on agricultural hybrid electric vehicles, which are solely based on simulation.

The rest of this work proceeds as follows: The project's background and modelling are described in Section 2. In Section 3, an intelligent EMS is introduced for the ERSAPHT which includes a farm operation recognition algorithm (FORA) and multi-mode FLC. Simulations and experimental test results are described in Section 4. Finally, conclusions are drawn in Section 5.

2 | MATERIALS AND METHODS

2.1 | Experimental setup and tests' overview

This work is based on an extended-range solar assist plug-in hybrid electric tractor (ERSAPHT) as a renewable energy-based off-road vehicle that has been developed for agricultural light applications. In fact, this off-road vehicle is being used as a test bench for different projects related to agricultural applications [38]. According to Figure 1, the driving system of the ERSAPHT set-up consists of three electric motors (two for each driving wheel and one for the PTO and lifting system). The main characteristics of the vehicle are listed in Table 1.

The power supply system involves a lead-acid battery pack, biogas-fuelled engine generator (Bio-Gen), and on-board photovoltaic (PV) array to meet the energy demand from the electric motors. The battery pack, as the primary energy source, is directly connected to the DC bus. The Bio-Gen and the PV systems, as auxiliary power sources, are linked to the DC bus via AC-DC and DC-DC converters, respectively. It should be noted that the PV system helps the battery pack with energy supply. The total amount of energy that can be received from the installed PV system is 4.17 kWh per day [4]. Nonetheless, this free renewable energy source is insufficient for responding to all the power requirements because of its low power density. Therefore, the Bio-Gen system has been added to prevent energy shortage in the hybrid powertrain. Due to the existence of multiple power sources with different energetic characteristics, an EMS needs to be developed to split the power among the energy sources. The ERSAPHT's velocity and global position are measured by using encoders and GNSS modules. The data measured by different sensors along with driver commands could be recorded into an SD card by the data

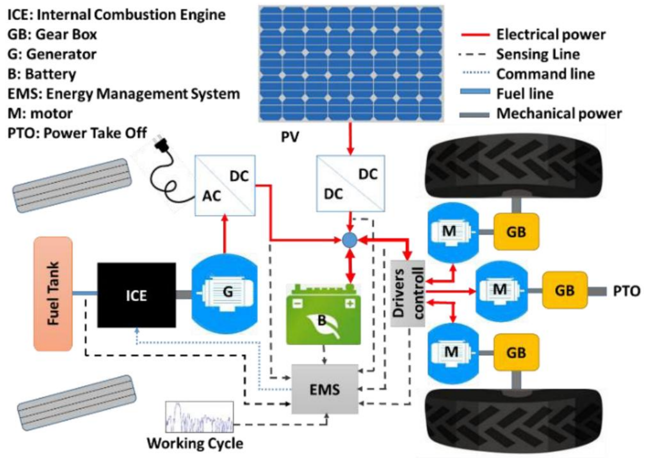


FIGURE 1 Simplified model architecture block diagram of the extended-range solar assist plug-in hybrid electric tractor

TABLE 1 The extended-range solar assist plug-in hybrid electric tractor's main characteristics [38]

Battery type	Lead acid
Battery specifications (Lead Acid)	80 V, 210 Ah
Fuel type	Biogas
Electric drives' maximum output power	21 kW (+15 kW for PTO)
Bio-gen rated power	8.8 kW
Bio-gen fuel consumption (at Rated Power)	0.35 m^3/kWh @ STP
PV system's output pick power	660 W
Total mass	2100 kg
Maximum speed	25 km/h

acquisition system. Furthermore, this vehicle is equipped with a portable computer which makes the design and implementation of an EMS possible, while having access to different measured data.

The inputs of the EMS module should be based on some initial data; the units such as current sensors, voltage-measuring modules, and user comments. These inputs are processed in the EMS in such a way, the measured current and voltage can be used to estimate the SOC of the battery pack and the required power. Furthermore, the outputs are transferred to the engine control module to control the Bio-Gen.

As mentioned before, a tractor is usually designed for towing different implements for transportation and farm field working. In transportation applications, the tractor is normally used to haul a trailer on rural roads or fields. On the other hand, in fieldwork, such as in sprayers and seed spreaders, the PTO systems might be used simultaneously to drive the implement. In this regard, several real-world experiments that include the trailer (drawbar load), seed spreader, and the boom-type sprayer are conducted to derive some typical working cycles for farm hybrid electric tractor applications. In fact, these real-world working cycles contain different contributions of light, medium, and high-power demand working conditions

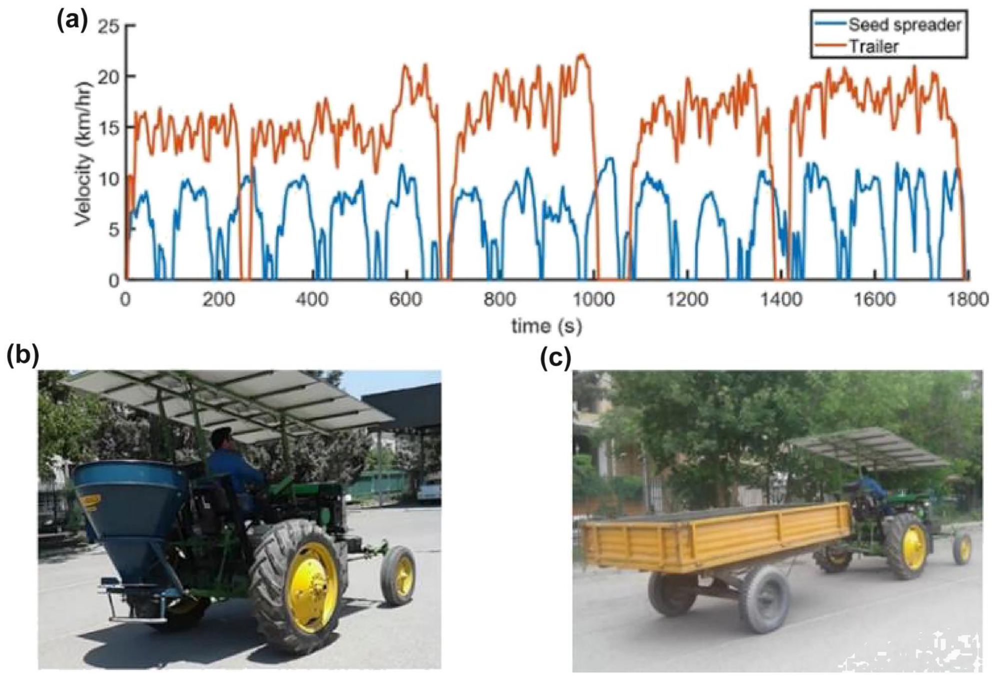


FIGURE 2 The extended-range solar assist plug-in hybrid electric tractor (ERSAPHT) in field experiments with typical implements working cycle: (a) Comparison of velocity profiles, (b) The ERSAPHT with the seed spreader, and (c) The ERSAPHT by pulling a trailer

based on measured data from the authors' previous research works [4, 38]. Figure 2 demonstrates the ERSAPHT in real-world field experiments with typical implements: Seed spreader and pulling a trailer. Consequently, the measured data are employed to design and evaluate the proposed EMS in this work.

Considering the literature, it is obvious that the model-based design is used as a powerful engineering aid tool to simulate vehicles in a computer before construction [1]. Therefore, a MATLAB Simulink model is used for designing and testing the EMS before its implementation on the experimental system to make sure that it does not cause damages during the experimental tests. The basic system components are modelled and evaluated in [38]; however, some fundamental aspects are summarised in the following section:

2.2 | The ERSAPHT powertrain modelling

In order to model the ERSAPHT powertrain, specific components, such as the battery pack, Bio-Gen, and electric machines, are considered with different levels of modelling complications, such as physical models, lookup table data, and efficiency maps provided by the manufacturers and the experimental test results. This approach is the most widely used methodology in the powertrain modelling of HEVs [4, 37, 38]. Figure 3 shows the longitudinal forces that affect a tractor during operation. In this regard, considering the speed (V) and mass (m) of the ERSAPHT, the traction force (F_{tr}) can be calculated to overcome the resistive force (F_{res}) as follows:

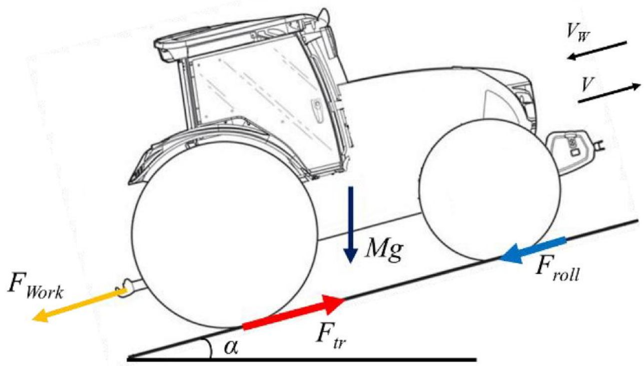


FIGURE 3 Tractor's longitudinal forces

$$m \frac{d}{dt} V = F_{tr} - F_{res} \tag{1}$$

$$F_{res} = F_{\text{roll}} + F_{\text{air}} + F_{\text{hill}} + F_{\text{work}} \tag{2}$$

$$\begin{aligned} F_{res} = C_{\text{roll}} \,.\, m \,.\, g + \frac{1}{2} \rho A C_d \left(V + V_w\right)^2 \\ + m \,.\, g \,.\sin\alpha + F_{\text{work}} \end{aligned} \tag{3}$$

where F_{roll}, F_{air}, and F_{hill}, denote the rolling resistance, aerodynamic drag, and hill climbing, respectively. F_{work} consists of the implement draft (F_{Drawbar}) and PTO forces (F_{PTO}) for doing a specific task on the farm. C_{roll} is the tyre rolling resistance coefficient; g is the gravity acceleration; ρ, C_d, A, and V_w are the air density, drag coefficient, frontal area, and wind velocity, respectively. α is the road or field slope.

The electric motors' power is given by a steady-state map as a function of the outputs' torque T_m and speed n_e of the motor. The vehicle requested power (P_m) from the electric motor side can be then expressed as

$$P_m = f\,(T_m.n_m) = F_{tr}\ V/\eta_m\eta_t \tag{4}$$

where η_m and η_t denote the motor and transmission average efficiency, respectively. Regarding the battery model, the equivalent circuit approach is used with a coulomb counting approach for the battery pack SOC (SOC_{Batt}) estimation as [39]

$$SoC_{\text{Batt.}} = SoC_{\text{Init.}} - \frac{100}{3600\ Q_{\text{Batt.}}} \int_0^t I_{\text{Batt.}}\ dt \tag{5}$$

where $SOC_{Init.}$, $Q_{Batt.}$, and $I_{Batt.}$ are the initial SOC, capacity, and output current of the battery pack, respectively. Since the purpose of this work is not to study the battery, the simplified relationship in [40] is used to determine the total battery power ($P_{\text{Batt.}}$).

$$P_{\text{Batt.}} = V_{OC}.I_{\text{Batt.}} - I^2_{\text{Batt.}}\ .\ R_{\text{Batt.}} \tag{6}$$

where V_{OC}, and $R_{\text{Batt.}}$ denote the open-circuit voltage and resistance of the battery pack, respectively.

Establishing an analytical Bio-Gen model is difficult to obtain. Therefore, it is common to use the fuel consumption map to describe a specific range extender as a fuel converter. This map can be determined by empirical procedures on a range extender test or can be computed by some software packages [41]. Therefore, the parameters suggested by the manufacturers are applied to the model as a lookup table. The engine fuel consumption rate ($\dot{m}_{\text{fuel}}$) is given by a steady-state map as a function of the Bio-Gen output power (P_{Genset}) at the operating point of the ICE outputs' torque T_e and speed n_e

$$\dot{m}_{\text{fuel}} = f\ (P_{\text{Bio-Gen}}) = f(T_e.n_e) \tag{7}$$

The power produced by the Bio-Gen can be computed from the fuel lower heating value (LHV_{fuel}) as follows:

$$P_{\text{Bio-Gen}} = LHV_{\text{fuel}}\ .\ \dot{m}_{\text{fuel}}\ .\ \eta_{\text{Bio-Gen}} \tag{8}$$

The output and input power from the battery pack are considered with negative and positive signs, individually. Therefore, the power delivered by the Bio-Gen and the PV systems are regarded as positive while the power captured by the traction and PTO systems are regarded as negative. Consequently, the total energy of the battery pack ($E_{Batt.}$) can be evaluated in terms of a time integral function of battery power (P_{Batt}), as denoted by the following equation:

$$E_{\text{Batt.}} = \eta_{\text{Batt.}}\left(\int_0^{t1}\eta_{PV}.P_{PV}dt + \int_0^{t2}\eta_{\text{Bio-Gen}}\ .P_{\text{Bio-Gen}}dt - \int_0^{t3}2P_m dt - \int_0^{t4}\frac{P_{PTO}}{\eta_{PTO}}dt\right) \tag{9}$$

where η_{Batt}, η_{PV}, $\eta_{\text{Bio-Gen}}$, and η_{PTO} denote the battery pack, PV system, Bio-Gen, and the PTO motor efficiency; $t1$, $t2$, $t3$, and $t4$ are the charging-discharging time intervals for the PV system, Bio-Gen, propulsion motors, and the PTO motor, respectively.

Moreover, the electric energy discharged from the battery needs to be recharged back in the future. This is equivalent to a certain amount of fuel consumption by the Bio-Gen set. In order to calculate the battery equivalent fuel consumption ($\dot{m}_{f.Batt.}$), the average values (battery charge efficiency (η_{charge}) and average efficiency of Bio-Gen set) are used in the following expression:

$$\dot{m}_{f.\text{Batt.}} = \frac{E_{\text{Batt.}}}{LHV_{\text{fuel}}\ .\eta_{\text{Bio-Gen}}.\ \eta_{\text{charge}}} \tag{10}$$

Eventually, the total equivalent fuel consumption at a given time can be expressed as the sum of the Bio-Gen set fuel consumption and the battery pack equivalent fuel consumption. In fact, this provides a unified representation of the energy used by both the fuel and the battery.

Due to multiple power sources of the plug-in hybrid series architecture of the ERSAPHT, it offers the opportunity for multiple operating modes by a downsized Bio-Gen. This allows the biogas fuelled Bio-Gen to operate in its high-efficiency region (recommended by the manufacturer) with a constant fuel consumption rate. Therefore, the battery is charged mainly when the vehicle is plugged into the electricity supply network, which reduces fuel cost if the electricity is supplied from a renewable source and potentially improves the overall energy efficiency. However, these multi-power source systems require an appropriate EMS to satisfy vehicle performance in the accepted working range that is described in the following section:

2.3 | Energy management system overview

In general, the proposed EMS in this work aims at operating the Bio-Gen and battery together throughout the work to keep the Bio-Gen in its most economical fuel consumption zone while reaching a reasonable range extension. The general architecture of the proposed EMS is shown in Figure 4. It comprises two main layers, namely FORA and multi-mode fuzzy logic controller (MFLC). The FORA is employed to determine the working condition mode at each classification interval, and consequently, activates the most appropriate mode of the MFLC (light, moderate, and heavy) to satisfy the demanded power. Each layer of the proposed EMS is described in detail in the following sections:

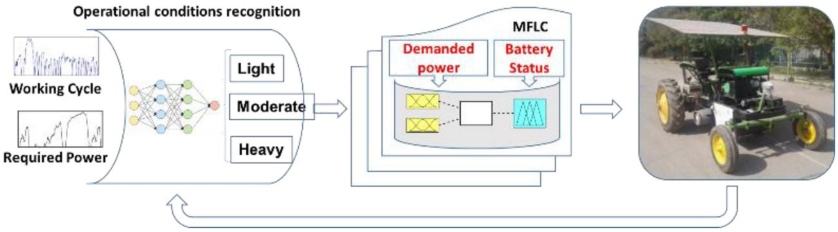


FIGURE 4 The overall view of the energy management strategy' layouts

TABLE 2 Mean of parameters for three specific modes by the designed farm operation recognition algorithm

Farm operation condition	Mean velocity (km/h)	Mean power (W)
Light	5.57	4240.35
Moderate	8.55	6379.63
Heavy	14.82	10,893.25

2.3.1 | Farm operation conditions' recogniser

In agricultural tractors, energy consumption in different tasks depends on various factors, such as machine types, farm environment, and operating conditions. These conditions can be repeatable duties during a working day that includes transportation and farm tasks. For instance, during a spraying operation as a farm task, the machine usually utilises both the auxiliary power take off (PTO) and the traction system power while a trailer pulling operation uses the traction system solely. Therefore, it seems that there is a classification potential due to differences in the working cycle's features. Parameters such as required power, speed range, operations' idle time, and PTO usage can be selected as clustering features.

Literature consideration shows that the FCM approach is one of the most famous unsupervised classifiers which has reasonable accuracy and computational time for a real-time pattern recognition [42]. The FCM allows the classification of one set of data into several clusters in the pattern recognition methods. Therefore, the FCM as a reliable method is applied to classify each working segment into the three considered working modes (light, moderate, and heavy) by extracting the statistical features from the measured data. In addition, Table 2 lists the velocity and required power mean values for the clustered data. It can be found that the difference between various clusters is clear and the FCM can get satisfactory precision in current condition recognition as a part of the FORA. In addition, on conditions like a short working path or at the beginning of work, there is not enough data to determine the appropriate working mode. Therefore, to failover that problem, the moderate mode is defined as the default mode by the EMS to put vehicle performance as a priority on an unrecognised condition. Moreover, when a new working mode is identified three times, consecutively, the same recognition is perceived as correct.

In this work, to select the number of clusters for the extracted features from the measured farm driving cycles, the silhouette criterion is employed. Silhouette value interprets and validates the consistency within clusters of data. It measures how close each point in one cluster is to points in the neighbouring clusters. A larger silhouette value shows better clustering. The silhouette value (S) is between −1 and +1 and can be defined for each datum (i) as follows [43]:

$$s(i) = \frac{b(i) - a\,(i)}{\max\{b(i).\,a\,(i)\}} \tag{11}$$

where a(i) denotes the average distance from the i_{th} point to other points in its cluster, b(i) is the average distance from the i_{th} point to the points in the other closest clusters. The silhouette value has been calculated for a different number of clusters, employing mean power and mean velocity working features, as shown in Figure 5. This figure illustrates that the maximum amount of silhouette value is reached by choosing three clusters of the working mode.

After having the number of clusters from the silhouette value, each of them is composed of the working segments nearest to the centre of the cluster. The distance between each cluster centre and each working segment is calculated based on the Euclidean distance (ed(x,y)) as an operation condition recogniser by the following equation [28]:

$$ed(x.y) = \sqrt{\sum_{i=1}^{n} \left(x_i - y_i\right)^2} \tag{12}$$

where x is the cluster centre vector, which is three in this work, y is the working-segment vector, and n is the number of working features. The distance between each cluster centre and all the working segments are calculated and then the working segments nearest to the centre are combined to reach an almost 1800-s representative measured working cycle for every cluster. Every working segment has a degree of belongingness to each farm operation condition cluster, specified by a degree of membership between 0 and 1. Thus, each working segment that has a greater membership degree is more meritorious to be chosen by the FORA as a working mode. In this regard, a sampling window of measured data between 50 and 150 s is

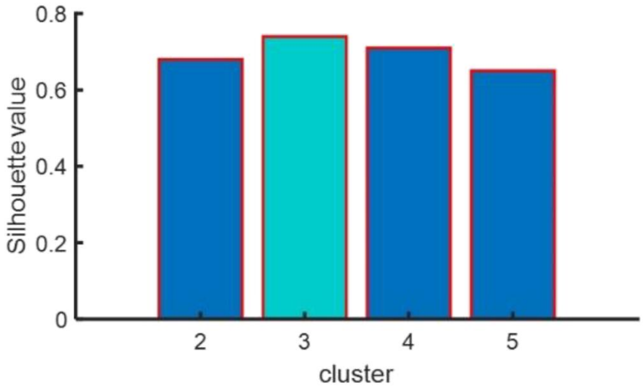


FIGURE 5 Silhouette value for each number of clusters

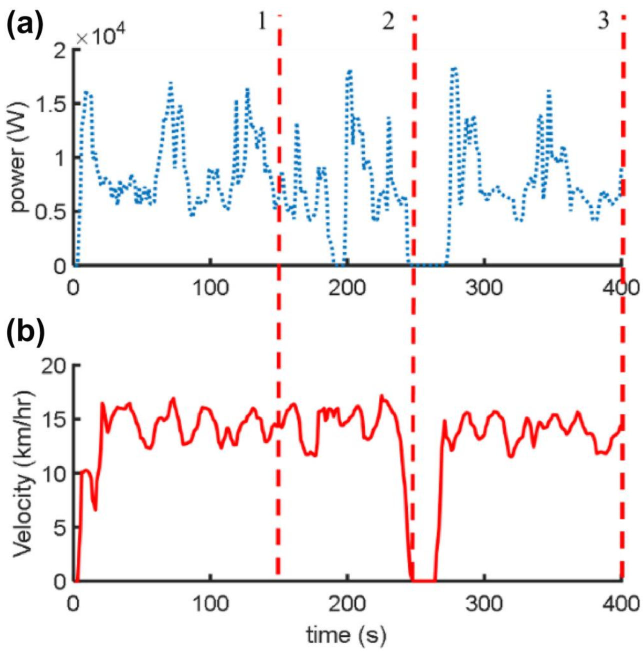


FIGURE 6 Typical measured working cycle and working-segment samples in the trailer's working cycle, (a) required power, (b) velocity

employed, and it is updated every 50 s to extract the statistical driving features while avoiding frequent mode switches [44]. Therefore, the FORA decomposes the working cycles into a working segment on the condition that an idle time is detected after 50 s while elsewhere the working segment goes up to 150 s.

Figures 6 and 7 and show the principle of separating experimental data into working segments for two typical working cycles measured by the trailer and the seed spreader. By comparing the working cycle in these figures, it is obvious that the tractor speed and the required power in the trailer cycle (Figure 6) are usually higher along with more continuously travelling time depending on road conditions. However, in the seed spreader's working cycle (Figure 7), it turns out that the operations are almost repetitive while the average required power is lower in each working segment compared to the trailer's working cycle. Moreover, it should be considered that

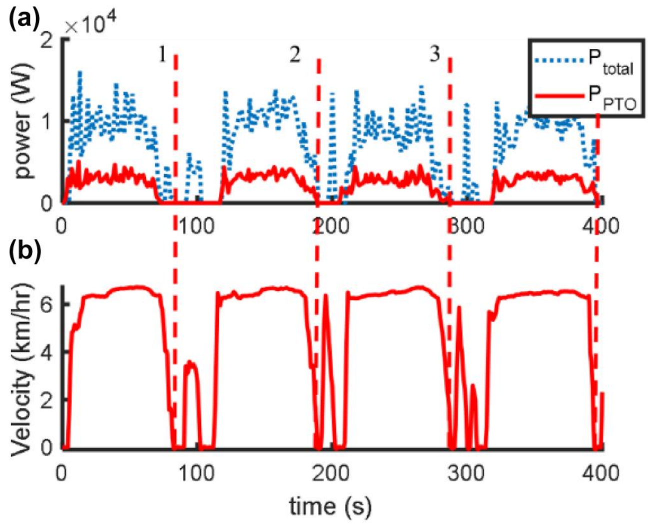
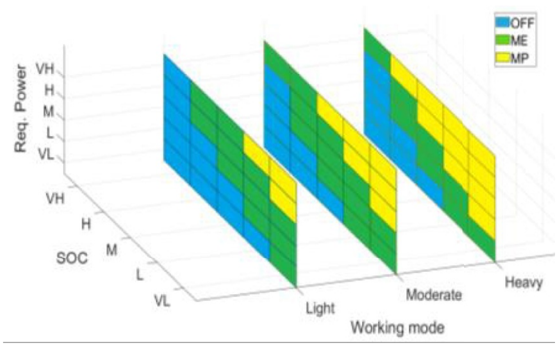


FIGURE 7 Typical measured working cycle and working-segment samples in the seed spreader's working cycle, (a) required power (total and PTO), (b) velocity

the PTO does not work at the end of the roundabout. Consequently, the operating condition mode determined by the FORA can be used by the MFLC's energy management strategy (EMS) which is explained in detail in the next section.

2.3.2 | MFLC EMS

Many factors, such as non-linear behaviour of vehicle components and unidentified behaviour of exogenous variables (farm condition, weather, driver behaviour), can lead to the complexity of an EMS design for an agricultural hybrid electric tractor. Also, the FLC provides strategic rules by using linguistic labels to integrate the knowledge of an expert into the design procedure and does not require a precise model of the system. Therefore, FLC is one of the best options to deal with these uncertainties while designing an EMS for the ERSPHAT. In this regard, a multi-mode fuzzy logic controller (MFLC), composed of three modes, is designed to embrace the requirements of each farm operating condition in the second stage. Each FLC mode considers the requested power and battery SOC level as inputs to determine the power required by the Bio-Gen in the output. Figure 8 presents the rule base of the proposed MFLC with respect to the two inputs (required power and battery SOC) and one output (power demanded by the Bio-Gen). For the SOC and the requested power, five membership functions (MFs) are considered, namely very low, low, medium, high, and very high ranges. Furthermore, the OFF, maximum efficiency (ME), and maximum power (MP) are represented by blue, green, and yellow colours, respectively, for the Bio-Gen modes as the output MFs. The FLC inputs go under the fuzzification process to be mapped between 0 and 1. Then the decision-making unit by means of fuzzy reasoning rules determines the FLC output values between 0 and 1.



VL = Very Low
L = Low
M = Medium
H = High
VH = Very High
ME = Max. Eff.
MP = Max. Pow.

Moderate mode output		SOC				
		VH	H	M	L	VL
Req. Power	VH	ME	ME	MP	MP	MP
	H	OFF	ME	ME	MP	MP
	M	OFF	ME	ME	ME	MP
	L	OFF	OFF	ME	ME	ME
	VL	OFF	OFF	OFF	ME	ME

FIGURE 8 Fuzzy logic controller rules and table description for moderate mode as an example

Ultimately, this data goes under a de-fuzzification process to be converted into real value for the Bio-Gen control unit to control the ICE's throttle position. The specifications of the defined MFLC are as follows: the fuzzy system type is Mamdani, the inference engine is AND (minimum operator) and de-fuzzification is the centroid.

Figure 8 represents the control rules, which are based on the expert experience. The objective of the rules is to employ the Bio-Gen in its maximum efficiency or maximum power to help the battery depending on the requested power and SOC level; otherwise, the battery will provide the power solely. For example, the MFLC decides the power split between the battery and the Bio-Gen based on the vehicle's power demand and SOC as follows: (1) when a working mode is recognised as heavy and the battery SOC is high while the operation power requirement is low, only the battery is used to supply power. (2) When the working mode is recognised as moderate and both SOC and requested power are high, the battery will help the Bio-Gen provide the power until the SOC falls to its lowest limit. (3) When the working mode is recognised as light and the SOC is more than the low level, whereas the operation power requirement is low, the Bio-Gen will remain off. Therefore, in these modes, the Bio-Gen will provide the power demand as a range extender and emergency power provider.

Indeed, at the beginning of the light working mode, the EMS uses the charge depleting (CD) control strategy when the battery SOC is at high levels. In this mode, the motor propels the vehicle using the electricity from the battery pack without the assistance of Bio-Gen until the battery SOC reaches the minimum level. However, during the heavy working mode, the charge sustaining (CS) control strategy is hired by the EMS so that the Bio-Gen assists the battery pack in propelling the vehicle motors and charging the batteries. Meanwhile, during the moderate working mode, the charge blending (CB) control strategy is utilised by the EMS to propel the ERSAPHT.

The proposed supervisory MFLC that is applied to the EMS of the ERSAPHT can achieve effective control. However, due to the characteristics of the fuzzy control, the membership function of the FLC, which is based on experts' experience cannot achieve optimal control. As mentioned before, the FLC's performance could be improved by optimising its parameters for specific driving conditions using an optimisation algorithm. In this regard, genetic algorithms (GAs) are adaptive heuristic search algorithms based on the evolutionary ideas of natural selection and genetics in order to provide solutions to real-world problems. Specifically, the GA is applied in order to solve several optimisation problems, such as problems where the objective function is discontinuous, non-differentiable, stochastic, or highly non-linear [45]. In this regard, GA has become one of the most important algorithms among modern optimisation algorithms because of its good global search performance and low algorithm complexity [46]. Since the comparative analysis of this work is mainly based on specific real working cycles, the proposed fuzzy controller's parameters are optimised by means of the genetic algorithm (GA) to achieve online near-optimal EMS for the known working cycles of the developed ERSAPHT.

2.3.3 | Genetic-fuzzy EMS

The optimisation of fuzzy MFs by GA is explained in other works [26, 46, 47] for on-road hybrid vehicle EMS problem. In this respect, for an optimisation problem's definition of some fundamental aspects such as objective function and constraints are necessary. However, it should be noted that each turn on of the Bio-Gen causes additional losses in terms of a higher quantity of injected gas to guarantee a stable engine burn process for the starting revolutions, larger applied electric torque to overcome static friction, compression work, and cold start effects. Therefore, the suggested GA-FLC is aimed at minimising the fuel consumption (m_{fuel}) and the number of engines ON/OFF (N) to provide the most efficient work and avoid frequent engine cold start. The input and output MFs' designing parameters, which equal to 26 in total, are used as decision variables for FLC optimisation. The GA uses certain natural procedures, such as crossover and mutation, to leave out the unfavourable populations and retain the most meritorious ones to generate new generations in order to perform the optimisation process [25]. In this regard, the process of survival of the fittest refers to the minimisation pattern of the given cost function. Consequently, the cost function and constraints in performing the MFs adjustment over each working mode are integrated as follows:

$$\min J_{GA} = \frac{1}{w_1 + w_2}\left(w_1 \int_0^t m_{\text{fuel}}\, dt + w_2 \int_0^t N\, dt\right) \quad (13)$$

$$D_{MF_{k.min}} \le D_{MF_k} \le D_{MF_{k.max}}\ (k = 1\cdots26)$$

$$MT \le P_{\text{Bio-Gen}} \le MP$$

$$0.2 \le SOC \le 1$$

where J_{GA} is the performance index for GA, w_1 and w_2 are the weighting variables that have been added to enforce the importance of the fuel economy and the number of engines ON/OFF that could be defined based on the design objectives. For instance, when the main objective is the minimisation of the vehicle's fuel consumption, its weight is set to 1 and the engine's ON/OFF weights are set to less than 1. However, both the objectives are equally important in this work. Therefore, the values of w_1 and w_2 have been defined as 2.35 USD/kg and 0.035 USD, respectively. These values are based on the 2020 Alternative Fuel Price Report by the U.S. Department of Energy [48]. D_{MF} denotes the degree of the parameter for defining the MFs for the FLC. In this case, the main GA parameters and constraints such as the iterative generations, the elite count, and the crossover probability are set to 100, 10, and 0.8, respectively. As the objective function includes two variables, in order to boost the algorithm's performance, the population size is defined as 150. Consequently, according to the main parameters of the GA, the rule base of the fuzzy controller can be optimised. Ultimately, the working cycle from the data experimentally measured by the ERSAPHT platform is used as input for the GA-fuzzy algorithm and the optimisation process has been carried out in the simulation model.

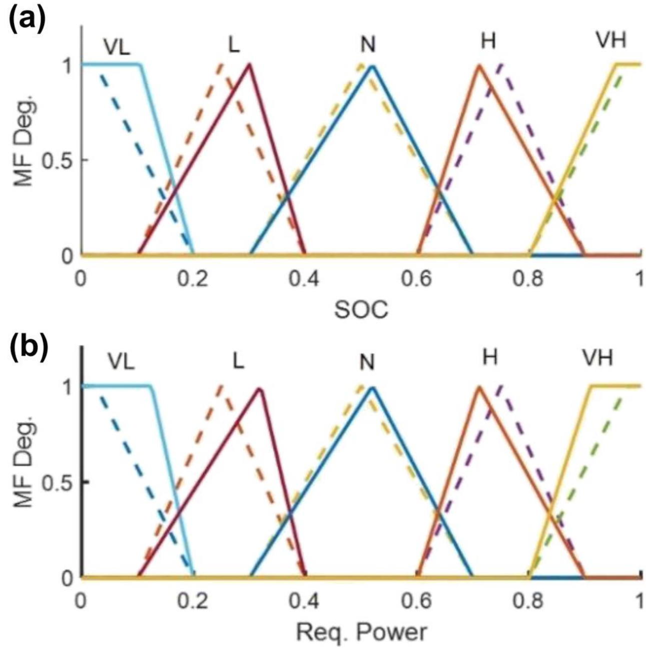


FIGURE 9 Optimised membership functions (MFs) (solid line) compared to the initial MFs (dash line) for the state of charge and requested power

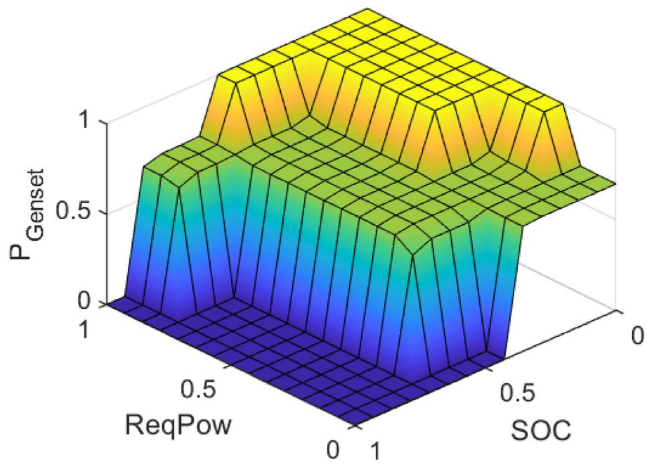


FIGURE 10 Control surface for moderate mode

Accordingly, the optimised fuzzy MFs compared to the initial ones are shown in Figure 9. In addition, Figure 10 shows the inference for the optimised FLC during the moderate working mode, which is obtained based on the battery's SOC and the required power. Moreover, for the ERSAPHT as a PHET, it is expected that the SOC reaches the lower limit (20%) at the end of the day as a constraint, so that the battery can be recharged by the power grid rather than by the ICE.

2.3.4 | Dynamic programing EMS

A global optimal solution can be achieved using DP for multi-constraints and non-linear dynamic systems. While this approach cannot be applied in real-time EMS applications, it can provide an ideal baseline for assessing different EMSs [49]. Therefore, DP is used to obtain the optimal results in this study and its results are compared with the developed GA-FLC EMS. Since DP is a classic method in HEVs and is available in other similar works, this section follows the developed DP in [26, 50]. By doing the calculation backwards over the time horizon on the basis of Bellman's principle of optimality [51], DP seeks for the optimal control action trajectory among all the possible offline actions by assuming that the driving cycle information is available [50]. The breakdown of the entire trajectory into multiple homogenous sub-trajectories is the key condition to apply DP. In this regard, the working cycle is broken down into N stages, and each stage corresponds to an individual state. Each stage needs to be attached to a state variable. In the discrete-time format, the PHET system can be formulated as follows:

$$x(k+1) = f(x(k).u(k)).\ k = 0.1.\ \dots\ .\ N-1 \tag{14}$$

where $x(k)$ is the state variable vector (SOC of battery $SOC(k)$), and $u(k)$ is the control variable (Bio-Gen requested power $P_{Bio\text{-}Gen}(k)$). Then, the optimal control problem is to obtain the control sequences to minimise the following cost function:

$$J_{DP} = \sum_{k=0}^{N} L\ (x(k).u(k)) \tag{15}$$

where $L(k)$ is the instantaneous cost. In fact, the optimal fuel consumption of the whole drive cycle can be determined by calculating the optimal fuel consumption of each state utilising (15). Accordingly, the objective function can be simplified to a single state variable SOC and a single control variable $P_{Bio\text{-}Gen}$. In summary, the energy management problem of the ERSAPHT is to seek a trajectory for $P_{Bio\text{-}Gen}(k)$ to make the objective function value minimum, while satisfying the requested power and other constraints. Therefore, the state variable can be expressed as follows:

$$\begin{aligned} SOC(k+1) &= SOC(k) + \Delta\, SOC(k) \\ &= SOC(k) + g\ (SOC(k).\ P_{\text{Bio-Gen}}(k)) \end{aligned} \tag{16}$$

In the optimisation process, some restrictions should be considered to ensure the safe operation of the components such as the battery, electric motor, and Bio-Gen. In the following equation, min represents the minimum value and max represents the maximum value of the variables:

$$\begin{cases} SOC_{min} \le SOC\ (k) \le SOC_{max} \\ T_{m-min} \le T_m\ (k) \le T_{m-min} \\ n_{m-min} \le n_m\ (k) \le n_{m-min} \\ T_{Bio-Gen-min} \le T_{Bio-Gen}\ (k) \le T_{Bio-Gen-max} \\ n_{Bio-Gen-min} \le n_{Bio-Gen}\ (k) \le n_{Bio-Gen-max} \end{cases} \tag{17}$$

where $T_m(K)$, $n_m(K)$, $T_{\ Bio\text{-}Gen}\ (K)$, and $n_{Bio\text{-}Gen}\ (K)$ are the speed and output torque of the electric motor and Bio-Gen units at the kth step from the related efficiency maps, respectively. In this study, the initial SOC is considered equal to 0.7. However, compared with HEVs, PHEVs have a larger battery and the battery acts as a power equaliser to improve the ICE's operating efficiency with the expectation of the same SOC at the start and end of a trip and can replace a certain amount of fossil energy with grid electricity [52]. Therefore, the minimum and maximum allowed SOC, defined as 0.2 and 1, respectively. Consequently, using the Bellman optimal theory, the objective function for the $(N-1)th$ step can be expressed as follows:

$$\begin{aligned} &J^*_{GA_{N-1}}(x(N-1)) \\ &\quad = min_{u(N-1)}[L\ (x(N-1).\ u(N-1)] \end{aligned} \tag{18}$$

For the kth state $(0 \le k < N-1)$, the objective function is

$$J^*_{GA_k}(x(k)) = min_{u(k)}\ L\ (x(k).\ u(k)) + J^*_{GA_{k+1}}(x(k+1)) \tag{19}$$

where $J^*_{GA_k}(x(k))$ is the optimal cost-to-go function at state $x(k)$ from the kth simulation stage to the end of the driving cycle and $x(k+1)$ is the state in the $(k+1)th$ step when the control variable $u(k)$ is applied to state $x(k)$ at the kth step. The errors that occur during the implementation of the DP procedure are closely related to the discretisation resolution of relevant continuous variables. Therefore, it is necessary for the variables to be discretised into finite points [52]. In this regard, the state variables have the same discretisation resolution which is chosen to be equal to the sampling period of measured working cycles (a time step of 10 ms). And the control variable is discretised to the number of possible values for the digitalised control variable [50]. Ultimately, the minimum value of the objective function can be determined based on the defined constraints to achieve optimum fuel consumption by using the simulation tool.

3 | RESULTS AND DISCUSSIONS

For farm tractor applications, the proposed EMS is supposed to work online without any prior knowledge about farm operation conditions. Therefore, a mixed working cycle is made up based on the conducted experimental test for three typical farm operations comprising trailer, seed spreader, and boom-type sprayer (each for 1800 s). The mixed working cycle consists of the tractor's speed profile, required traction power, and PTO power for the implements operation. Consequently, the ERSAPHT's performance has been analysed by employing the proposed FORA along with three energy management methods comprising the pre-defined MFLC, the optimised MFLC, and the thermostatic control strategy (TCS). The results from each layout of the proposed EMSs are discussed in the following sections:

3.1 | Operation condition recognition algorithm (FORA) results analysis

First, the mixed working cycle is used to assess the performance of the FORA. The results obtained in Figure 11 show that the FORA is capable of recognising new working conditions based on calculated features without switching or confusing between the conditions. As mentioned before, on conditions such as a short working path the required power swiftly changes from one mode to another, the recognition method might make a wrong decision that may affect the fuel economy. To avoid that problem, the moderate mode is defined by the EMS as the default mode (as shown in Figure 11) to put the vehicle performance as a priority on unrecognised conditions. For instance, at the beginning of running the operation, the moderate mode is selected by the FORA by default. Then the FORA continuously analyses the previous working section up to 150 s depending on the measured features. In other words, the working features are calculated for the past driving working segment, and then the calculated working features are compared with the pre-defined reference points, by using the Euclidean distance concept (Equation 11). The reference point nearest to the extracted working features is the most probable mode. After that, the FORA applies the most appropriate mode to the MFLC for a 50 s interval and the same process is continuously repeated for future sections. The recognition of a new working mode is perceived as correct when the mode is identified as same, three times consecutively.

Because of the principal target of this work, which is a reliable FORA for the EMS of the ERSAPHT, the percentage of correct recognition ($C\%$) has been investigated simply by the following formula:

$$C\% = \frac{n_c}{N_t} \times 100 \tag{20}$$

where, n_c and N_t are the number of correctly recognised sections and the number of all sections, respectively. Given that the working features are calculated for the past working section (working segment), the results of the investigated farm operation show that the condition's recognition of the designed FORA is correct by 81%, as shown in Figure 11. Obviously, it should be mentioned that in the actual farm working conditions, the equipment is not usually changed in the short term and it is typically constant for a working shift. Therefore, the FORA could recognise the appropriate mode with more accuracy in the actual farm working conditions (as an example, over 91% at the seed-spreader working cycle).

3.2 | Performance evaluation of the intelligent EMS based on experimental working cycles

The performance of the proposed MFLC is validated based on the experimental working cycles. In this regard, measured data from the three typical farm operations that were introduced in Section 3 is imposed on the designed EMS as input. The results in Figure 12 demonstrate the obtained traction power and the power provided by each energy source during the working cycles. This result shows the power provided by the battery pack,

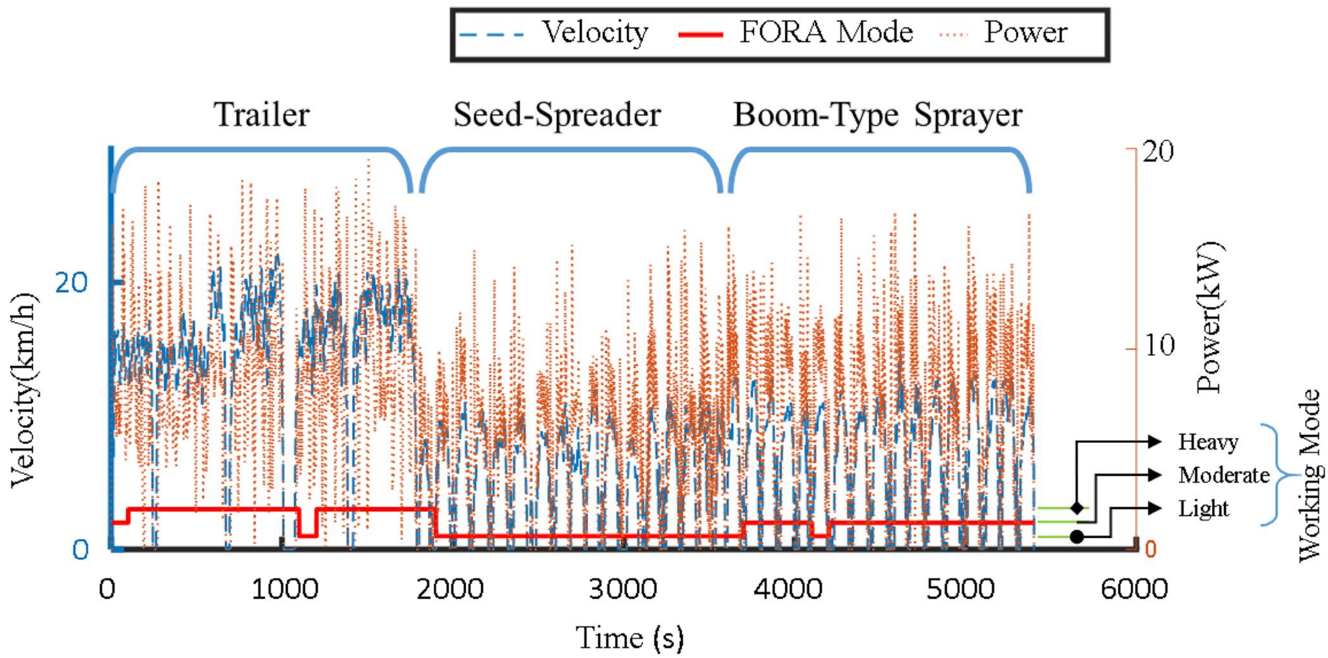


FIGURE 11 The farm operation recognition algorithm results for the typical measured data and mode recognition (1: light, 2: moderate, and 3: heavy)

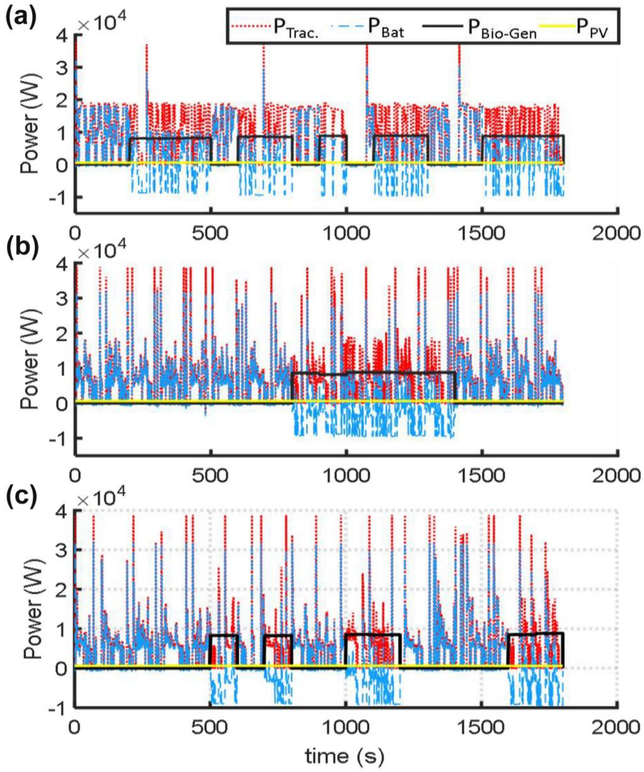


FIGURE 12 The obtained traction power and the power provided by each energy source during the working cycles, (a) Trailer puling, (b) Boom-type sprayer, and (c) Seed spreader

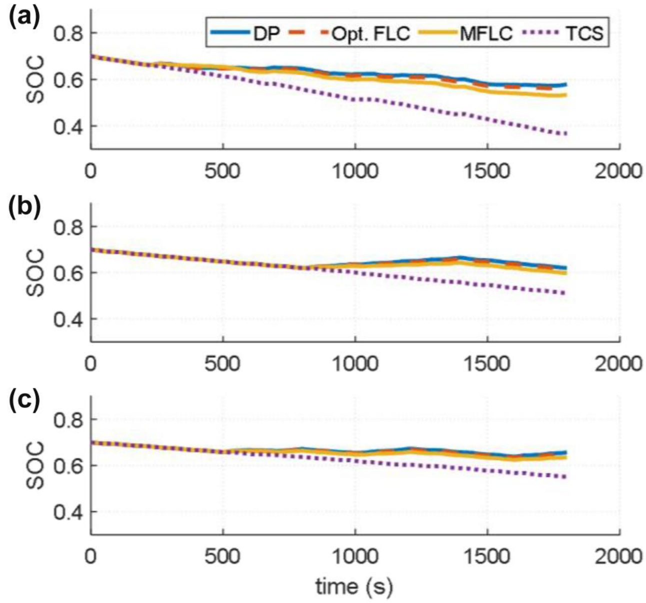


FIGURE 13 The obtained battery state of charge during the working cycles, (a) Trailer puling, (b) Boom-type sprayer, and (c) Seed spreader

PV, and Bio-Gen systems employing the MFLC as the EMS. In practice, the Bio-Gen systems either assist the battery pack to power the traction motors when the load power request is high or charges the battery pack when the load request is low. The results in Figure 12a show that the trailer's work cycle requests the highest power due to its higher speed and load compared to the other two cycles. Therefore, the EMS has used the Bio-Gen for a longer period in high-power mode (MP mode). Figures 12b and 12c illustrate that the Bio-Gen system has been employed by the EMS for a shorter time in a more efficient range (ME mode). From this figure, it is clear that the EMS avoids the unnecessary on-off cycles of the Bio-Gen.

The performance of the proposed intelligent EMS is compared with DP and a basic charge depleting rule-based EMS to evaluate its functionality before implementing it in a real vehicle. Figure 13 compares the battery SOC level obtained based on the pre-defined MFLC, the optimised GA-FLC, the DP and the thermostatic control strategy (TCS) during each working cycle. It is evident that the off-line optimal strategies (DP and optimised GA-FLC) are close and try to keep the SOC at a higher level than the two other rule-based methods because of their prior knowledge about the particular input working cycles. Also, the use of the Bio-Gen and battery pack together throughout the work helps the ERSAPHT operate in its more optimal region to avoid range anxiety and component fast degradation. Accordingly, the figures demonstrate almost similar results for both the optimisation-based EMSs. Moreover, it is obvious that the SOC of the pre-defined MFLC strategy is much closer to the optimal one compared to the TCS. As can be seen, initially only the battery pack provides the power to the traction subsystem until the battery SOC is higher than the threshold defined by the controllers (see Figure 12 also). Therefore, the battery SOC rate decreases during this period. However, when the Bio-Gen starts working, the slope of the SOC diagram decreases or increases depending on the EMS commands. Regarding Figure 13a, it is obvious that the SOC usually decreases during the trailer's working cycle while the Bio-Gen is still on. This is due to the fact that the Bio-Gen is a downsized range extender. Moreover, as can be seen in Figures 13b and 13c, the average power output of the Bio-Gen is closer to the power consumption of the sprayer and seed-spreader work cycles. Moreover, the slope of the SOC diagram in these operating modes increases when the Bio-Gen is turned on.

3.3 | The ERSAPHT's performance evaluation

Since the real-world tests have many limitations and the 1800 s test is too brief to provide an appropriate measure of the fuel economy in each mode, a longer test has been performed in the developed Simulink model. In this regard, the performance of the four EMS including the pre-defined MFLC, the optimised FLC, the optimal DP, and the TCS are compared by considering 10 h of daily working period with the fully charged battery pack. Consequently, each working cycle has been separately imposed on the simulation model.

Table 3 shows the performance of the ERSAPHT under three typical working cycles by employing design strategies based on the previously described real-world test data. According to these results, the power requirement for the seed

TABLE 3 The comparative performance of the extended-range solar assist plug-in hybrid electric tractor under three typical working cycles

			Fuel cons. (m^3) (performance improvement [%])			
Working cycle	**Recognised mode**	**Ave. power (kW)**	**TCS**	**MFLC**	**Optimal FLC**	**DP**
Trailer	High	11.85	1.083	0.955 (12)	0.903 (17)	0.898 (18)
Sprayer	Moderate	8.91	0.661	0.579 (12)	0.548 (17)	0.547 (17)
Seed Spreader	Low	6.96	0.540	0.470 (13)	0.442 (18)	0.441 (18)

Abbreviations: FLC, fuzzy logic control; MFLC, multimode fuzzy logic controller; TCS, Thermostat Control Strategy.

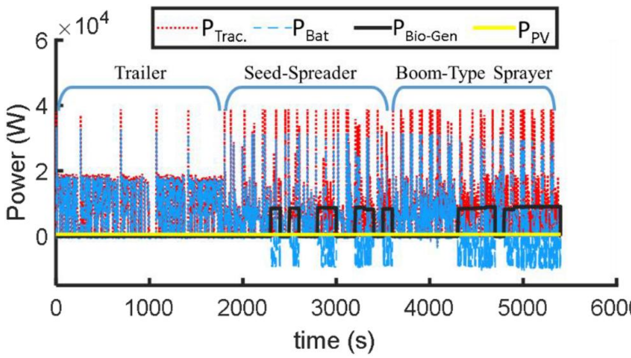


FIGURE 14 The obtained traction power and the energy provided by each energy source during the mixed working cycles

spreader is lower than the sprayer and the trailer; therefore, minimum fuel consumption is obtained due to less Bio-Gen working time, compared to the other working conditions. In this regard, the obtained results show that the TCS achieves less fuel efficiency because more fuel is consumed by the ICE during the employment of the Bio-Gen in the maximum power mode, compared to the other EMSs. Furthermore, the fuel consumption rate of the pre-defined MFLC strategy is obtained as 0.955, 0.579, and 0.470 m^3 in the operations of the trailer, boom-type sprayer, and the seed spreader, respectively. It illustrates almost 12% to 13% of fuel economy improvement. Moreover, the information on the table demonstrates an average difference of 5.5% in fuel consumption for the MFLC compared to the optimal strategies. According to these results, the pre-defined MFLC controller's performance is very close to the optimal strategy. However, it proves the proposed optimal GA-fuzzy strategy is capable of running the Bio-Gen system in the most efficient operation zone during the working time to achieve less fuel consumption.

Furthermore, the time required for performing the GA-fuzzy EMS optimisation process to tune the MFs is around 50 min, using a desktop running with an Intel (R) Core i7-5500 CPU and 16 GB memory. However, this process is performed once to calculate the optimised membership function parameters. The computation time of using this optimised strategy in real time is less than one second. Accordingly, the computation time for the off-line DP optimisation is around 45 s, while these numbers for the single FLC and TCS are less than one second. Consequently, based on the achieved results, the proposed GA-fuzzy EMS is suitable for the purpose of real-time implementation to reach a near-optimal EMS for the developed ERSAPHT.

In order to evaluate the reliability of the proposed intelligence GA-fuzzy multi-mode EMS, the combined working cycle presented in Section 5.1 is imposed on the ERSAPHT model as input. Consequently, the performance of the EMS is assessed in terms of energy usage from each source. The results obtained in Figure 14 show the power required by the ERSAPHT and the energy provided by each energy source during the mixed working cycles. These results illustrate that the proposed EMS behaves in an adapted way to minimise fuel consumption depending on the working conditions. Consequently, the developed algorithm in this work could be applied in a designed EMS to control the operation of the range extender on the safe operating condition to increase the components' lifetime and the fuel economy of the system.

4 | CONCLUSION

Literature consideration shows that there has been a trend towards the electrification of off-road vehicles such as agricultural tractors and mining vehicles by transferring key technologies from on-road HEVs. In this regard, the use of an advanced EMS has been a key factor for designing a hybrid electric powertrain for a PHET. This work proposes an intelligent EMS through the simulation of a farm energy independent off-road hybrid electric tractor using renewable energy sources (battery, PV, and biogas-fuelled Bio-Gen). The proposed EMS consists of two layers including a FORA based on the FCM classifier and an optimised MFLC based on the GA. Consequently, the FORA recognises the operation modes, namely light, moderate, and heavy. Then the most proper mode of multi-mode GA-Fuzzy EMS is activated to efficiently supply the power requested for the ERSAPHT based on the battery SOC and the required power. By employing this EMS, the Bio-Gen assists the battery pack at the lower SOC levels in supplying energy. This helps the Bio-Gen work in its efficient region to decrease fuel consumption and to increase the components' lifetime.

To evaluate the performance of the proposed EMS, three typical field experiments (trailer, boom-type sprayer, and seed spreader) were imposed in the ERSAPHT model. The achieved results verify that the proposed EMS can be used online efficiently in the studied off-road hybrid electric vehicle. To be more precise about the significance and applicability of the proposed pre-defined MFLC strategy, DP optimisation and rule-based TCS methods were used for comparison. It can be claimed that the fuel consumption in the GA-fuzzy EMS compared to the rule-based TCS declined around 17%, 17%, and 18% with the trailer, the boom-type sprayer, and the seed-spreader working cycles, respectively. Moreover, the reliability of the proposed EMS is tested when mixed power demand is subjected to the ERSAPHT model on the mixed working cycle. In this situation, the proposed intelligent EMS adapts to the current working mode and decreases fuel consumption compared to the rule-based TCS method.

CONFLICT OF INTEREST

There is no Conflict of Interest.

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