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Abstract: This work provides a basis for studying energy management optimisation in power-split hybrid electric vehicles (PSHEVs) to reduce fuel consumption and increase powertrain efficiency by enforcing a strategy related to battery level and vehicle speed. Three modes were used to operate the vehicle to meet different situations related to available energy and desired speed. These are particularly abundance mode, ascetic mode and optimal mode. For this, a system was designed based on several sub-models written in the discrete EVent system (DEVS) specification. The vehicle's power train and control strategy models were created in the DEVSimPy environment, and a joint simulation was carried out from the composite sub models until the overall model is reached. Simulation results under several driving cycles showed that the proposed system improves the energy consumption of the vehicle in different operating modes of the engines and gives more opportunities to adopt electric motors in vehicle transmission.

Keywords: hybrid electric vehicle; energy management; control strategy; energy management system; modelling and simulation; DEVSimPy environment.

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1 Introduction

Recently, the field of electric vehicles has gained significant attention among researchers, particularly concerning improving their energy management (Sabri et al., 2016; Adnan et al., 2018). Despite advances in hybrid electric vehicles (HEVs), using high-capacity batteries charged at electrical stations connected to the grid offers only limited driving distance (Tran et al., 2020; Chung et al., 2014). To counter the power distribution problem in HEV, energy management strategies are used, and they have inspired many researchers to discuss and suggest improvements. Most of these strategies use either optimisation (Kaleemullah and Faris, 2022) or a set of rules imposed on the vehicle's running system (Tran et al., 2020).

HEVs can be categorised into three types according to the way they are hybridised: series, parallel, and power split (Fan, 2007; He et al., 2012; Zhang and Mi, 2011; Liu, 2013; Murphey et al., 2013). This study focuses on the power split type, incorporating the benefits of both serial and parallel hybrids. The architecture of power-split hybrid electric vehicles (PSHEVs) is complex, and it requires a specialised control strategy (Baktayan et al., 2022), that is not adequately addressed by conventional control methods, such as optimal and robust control (Lee et al., 2017, Tran et al., 2020). The need for a more suitable control system arises when managing split powertrains in complex scenarios (Negadi et al., 2022). Initially, the control system relied on a rule-based approach to improve the fuel economy of the internal combustion engine (ICE) by compensating it with electric motors (Asfoor et al., 2014). It is possible to improve and correct this rule-based strategy, as it is developed through experiments with different scientific approaches, such as algorithms, frameworks, and intelligent designs, by subjecting them to modelling and simulation (Maatoug et al., 2023; Maatoug and

Belalem, 2014), and with new ideas and concepts (Xiong et al., 2021). For instance, the logic threshold method applied to the HEV control strategy optimises power distribution and maximises torque (Wang et al., 2015). Since driving performance is influenced by different driving cycles of the same PSHEVs, the control strategy must consider variables such as ICE power, electric motor power, vehicle speed, and state of charge (SOC) level (Ma et al., 2022).

Generally, in the control strategy, PSHEV operates according to three main modes, namely ascetic mode, optimal mode, and abundance mode (Wang et al., 2015). These modes are designed to deal well with the stored energy levels in order to fulfil the purpose of maintaining the level for as long as possible. This study aimed to enhance the efficiency and performance of the proposed rules-based energy management system through multiple experiments (Barlas, 1989). What this paper brings back is to answer the question how to create and improve algorithms through experiments. This can be achieved through formal modelling, which enables access and modification of the modelled system for improvement after repeated simulations (Gupta et al., 2011). The objective so is to develop and validate a rule-based HEV energy management strategy through modelling and simulation. By setting the motors' actuation points within an optimised operating range based on optimal adjustments to power consumption modes, the new control logic better adapts to uncontrolled power modes.

Most of the similar works showed the discussion of different experiments in order to prove the proposals and contributions, but they proceeded directly from the designed systems to the simulation, without showing a formal modelling of the constituent sub-systems, which gives a kind of legitimacy in how to prove its proposals (Fan, 2007; He et al., 2012; Zhang and Mi, 2011; Liu, 2013; Anbaran et al., 2014; Ahmed et al., 2020).

For example, the work presented in Anbaran et al. (2014) proposes system-level simulation and rule-based supervisory control strategies for split parallel hybrid electric vehicles, which can be considered as a family of parallel HEV powertrains. The advanced vehicle simulator (ADVISOR) is used to size and power-rate critical components of the PSHEV powertrain to meet specific performance constraints. It is better to program each atomic model component individually to best express its behaviour, rather than limiting yourself to parameter settings. The work presented in Ahmed et al. (2020) focuses on the performance results obtained by comparing two variants of a naturally aspirated gasoline engine and a hybrid electrically assisted gasoline engine using MATLAB Driveline. Comparative study analysing power output obtained from simulation. This article focuses on new-age hybrid electric technology that can deliver performance comparable to naturally aspirated engines. For performance tuning to go smoothly, it should be possible to add or remove subcomponents for modification, rather than just comparing different existing settings. The work in Ghorbani et al. (2007) discusses a simulation and modelling software package developed at the University of Manitoba, REVS: Renewable Energy Vehicle Simulator. REVS assists in detailed studies of HEV and plug in HEV (PHEV) configurations or energy management strategies through visual programming by creating components as hierarchical subsystems. Despite the advantages of visual programming in making changes, it is still written under MTLapSimpleLink where adding, deleting components, or changing their behaviour by changing programs is complex and difficult in such cases.

We use the discrete EVent system (DEVS) formalism (Zeigler et al., 2000) for the first time, for the formal modelling of the power management and control system of

HEVs, and is very reliable in terms of giving possibility to change the proposed designs. Atomic constituent subsystems are formed, which are then linked to form larger coupled models until the entire system is modelled whatever the size. The behaviour of each component sub-model is expressed by a program that can be modified if we wish to improve its behaviour in the global model. By clicking directly on the atomic model, the corresponding program can be seen where we can change anything in the program. This modelling method was chosen due to its ability to model any system, regardless of its complexity.

We did not find all these characteristics and advantages in similar works that we have seen, and even the most recent works, so we wanted to change the method of improving proposals to an official and reliable form, which gives us complete smoothness in making changes in all aspects, through the full exploitation of the power of programming in conception and validation.

We summarise the main contributions of this work as:

- Development of a two-layered control system that transmits movement to the wheels on the first layer and optimises energy consumption by implementing rule-based strategies on the second layer.
- Formal modelling of all subsystems according to the DEVS formalism in order to reveal their behaviour, in order to test the system through repeated simulations and make the necessary changes to improve it, taking into account measurement and modelling errors. (Huang et al., 2015).
- Conducting traffic simulations over multiple driving cycles to enhance energy management, focusing on searching for an optimal strategy through simulations instead of conducting multiple driving cycles in reality.

This approach differs from most current energy management studies in that it searches for an optimal strategy across various scenarios, reduces estimation errors, and enhances the reliability of the obtained control strategy. The simulation results demonstrate the efficacy of this approach, which has been refined through multiple experiments and modifications.

The paper structure arrangement is as follows:

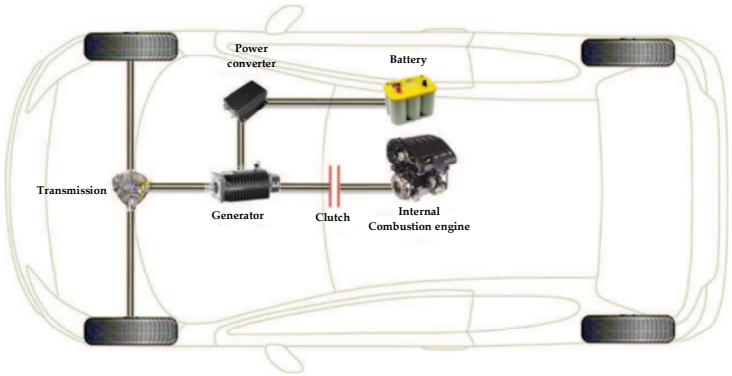
Section 2 gives an overview and a detailed explanation of hybridisation topologies in HEVs, especially series, parallel, and split-power. The system form of the PSHEV and the power train model are disclosed and explained in detail in Section 3. In Section 4, an energy management strategy for PSHEV is proposed in the form of algorithms that change energy consumption modes according to the status of the batteries. In Section 5, all the subsystems present are modelled according to the DEVS formalism. Furthermore, in this section, using the DEVSimPy simulator, the general model was implemented after programming all the atomic systems, each according to its behaviour in Python. Section 6 includes and discusses the results of the simulations, in particular the speed obtained throughout different driving cycles, the sources of the propulsion forces and the comparison of the torque of the different engines during one driving cycle, and the energy consumed in the different modes. Section 7 discussed conclusions and future work.

2 Hybridisation topologies in electric vehicles: an overview

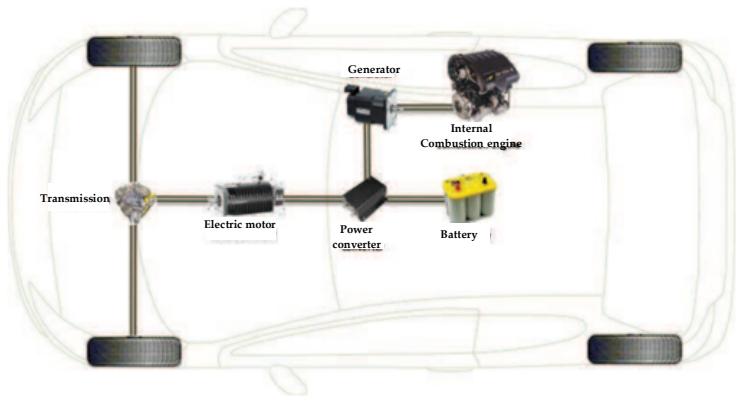
HEVs have characteristics of both electric and diesel engine vehicles. The ICE in HEV power trains is downsized and assisted by an electric motor for improved fuel efficiency and reduced exhaust emissions. Different HEV models have varying degrees of hybridisation, which refers to the level of independence of the power source in the power train.

Practically, the most common approach to categorise HEVS power train architectures that relies on a combination of power generated by electric motors and ICEs, is one that divides them into series, parallel, and power split topologies (Figure 1) (Ravey, 2012). In power-split architecture, such as the PSHEV in this study, both the electric motor and the ICE are used in a mechanical coupling to transmit motion to the wheels.

Figure 1 HEVs topologies: (a) parallel topology; (b) series topology and (c) power-split topology (see online version for colours)

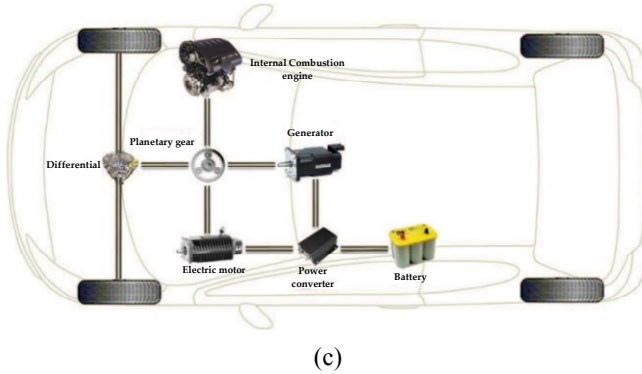


(a)



(b)

Figure 1 HEVs topologies: (a) parallel topology; (b) series topology and (c) power-split topology (see online version for colours) (continued)



This configuration, where the electric motor is integrated with the wheels, and the diesel engine directly drives them, is the most commonly used structure in the automotive industry (Song, 2018). It differs from the traditional configuration, where the electric motor is separated from the wheels, and the diesel engine is solely responsible for driving the vehicle.

An integrated starter generator (ISG) (Friedrich and Girardin, 2009) generates electricity for the engine or charges the battery pack. Because they are environmentally friendly and due to the risk of the disappearance of oil, which is incidentally on the way, modern HEVs have drawn the attention of many researchers and automotive engineers in recent years. HEVs are generally similar to standard HEVs and have a range similar to conventional vehicles, but they differ because they have a large batteries pack that can be charged from the grid (Tran et al., 2020). In limited driving conditions such as city traffic, ICE plays a significant role in propelling the powertrain. During periods of idling, the battery pack can be recharged using a battery charger plugged into a standard outlet. In such cases, the electric motor starts the vehicle when the batteries SOC exceeds the minimum allowed level. Both motors are used during rapid acceleration that requires a significant amount of power to meet the driver's demands (Xun et al., 2018). Whatever the topology, the fuel consumption is directly related to the driving cycle of the vehicle and its speed. On the highway, the fuel consumption is very good because the vehicle relies mostly on electric motors during constant speed, but in the city, where the ICE provides almost all the power; the fuel consumption is the same as in a conventional vehicle because the electric motor is only used for starting (Silvas et al., 2016).

3 System design and characterisation

A vehicle's powertrain consists of all the components that propel it forward. It converts energy from the electric or diesel motors into movement by the wheels. The power-train includes an ICE, an ISG, electric motors, and a large capacity battery pack (Peng et al., 2017). The transmission is a crucial component of the vehicle that regulates the power sent to the wheels, adapting it to driving conditions. It transfers power from the engine to the wheels.

The energy distribution of the power train components is shown in the following situations (Ravey, 2012):

- *Starting*: The vehicle uses electric motors only, and all power is drawn from the batteries through the power converter.
- *Acceleration*: During acceleration, two transmission sources are used: the electric motors, which draw power from the batteries, and the ICE power source, which adds two torques to provide power to the vehicle; But at the beginning, the use of ICE is more than electric motors in order to preserve electrical energy.
- *Steady speed*: At a steady speed, the ICE can recharge the batteries using the ISG, which converts the rotational motion of the ICE into the electrical energy needed by the vehicle. Specialised generators allow the ICE to operate at its most efficient point compared to parallel configurations.
- *Deceleration*: At the beginning of deceleration, the electric motors are highly relied upon, and after the vehicle slows down, both engines, whether electric or ICE, are dispensed with.
- *Braking*: During braking, the current is fed back to charge the batteries using the generator.

3.1 Control system design

The current study designed a model for energy-saving plug-in hybrid electric vehicles based on the PSHEVs described in Section 2. The model (Figure 2) includes a power train layer and an additional control layer to enhance the energy consumption system's rule-based energy management strategy.

The control layer has two subsystems: the speed controller subsystem and the energy management strategy subsystem. The speed controller subsystem sends the required speed torque value to the energy management strategy subsystem, which then adjusts the vehicle's movement parameters based on the batteries charge level and actual vehicle speed. The power train layer of a series-parallel HEV has five operating modes to drive the wheels (Shuai et al., 2019).

Figure 2 show that electric motors provide power at startup. The first scenario depends on the power required by the vehicle during steady driving and acceleration. In the first scenario, the ICE starts when the required power is equal to what the ICE can deliver at its optimal operating point. In the second scenario, when the required power is less than what the ICE can deliver at its optimal operating point but higher than what the electric motors alone can deliver, the ICE starts to drive the wheels, with any remaining power flowing through the ISG to recharge the batteries (Frijlink et al., 2001).

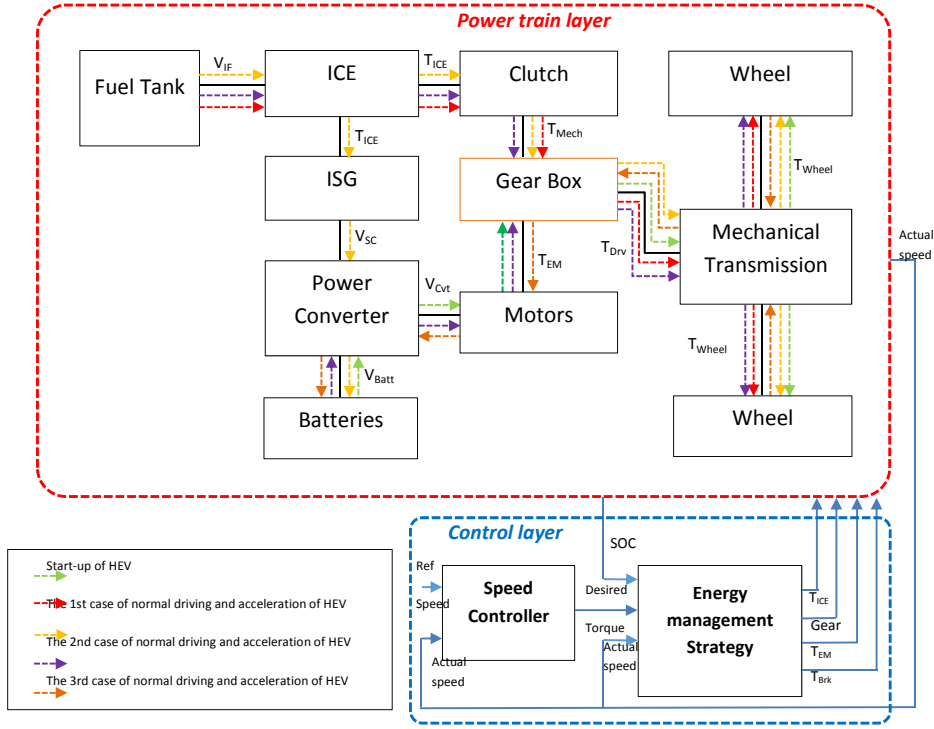
In the third scenario, both the ICE and the electric motors are used when more power is required than the ICE can provide. Finally, during deceleration, the electric motors act as generators, recharging the batteries through regenerative braking as needed.

3.2 Features of the PSHEV

In this part, we will consider the vehicle's characteristics, which serve as the basis for determining the parameters used in our research. These values have been widely

discussed in similar studies (Liu, 2013; Xiong et al., 2021; Ma et al., 2022; Xun et al., 2018).

Figure 2 Power-split hybrid vehicle system design (see online version for colours)



In Table 1, the main parameters of the PSHEV variants are presented. The ICE boasts a maximum power output of 137 kW and a maximum torque of 650 Nm. The ISG motors have a maximum power of 42 kW and a maximum torque of 400 Nm, while the traction motors have a maximum power output of 144 kW and a maximum torque of 1650 Nm. Five batteries are used, the capacity of one battery is 75 Ah with a voltage of 580 V. The PSHEV's traction is calculated based on wind direction, wheel diameter, roll resistance, drag coefficient, and primary reduction ratio.

These characteristics and parameters are the variables and their values that were dealt with in all stages of our project, from the beginning of writing algorithms, to modelling, to programming to simulation. The corresponding speed and torque equations when the clutches are closed are (Wu et al., 2017):

$$T_{ICE} + T_{ISG} + T_{EM} = T_{axle} \quad (T_{ICE} > 0) \quad (1)$$

$$W_{ICE} = W_{ISG} = W_{EM} = W_{axle}$$

where T_{ICE} , T_{EM} , T_{ISG} , and T_{axle} are the torques from the ICE, electric motor, ISG, and transaxle, respectively. W_{ICE} , W_{EM} , W_{ISG} , and W_{axle} represent reasonable speeds for the ICE, traction motor, ISG, and T_{axle} , respectively. In this work, the clutch is engaged while the PSHEV is in motion when the speed W exceeds 7.55 m/s, which means that the ICE

and electric motors work together to counteract the T_{axle} . When the clutch is disengaged, the equation is described in Wu et al. (2017):

$$T_{ICE} = T_{ISG} = T_{EM} = T_{axle} \quad (2)$$

$$W_{ICE} = W_{ISG}, W_{EM} = W_{axle}$$

Regenerative braking is allowed when the PSHEV is decelerating. During regenerative braking, T_{ICE} and T_{ISG} are set to 0, while T_{EM} is always equal to T_{axle} (Wu et al., 2017). Only the electric motor is utilised for charging when the PSHEV is slowing down.

$$T_{ICE} = T_{ISG} = 0, T_{EM} = T_{axle} (T_{ICE} < 0) \quad (3)$$

$$W_{ICE} = W_{ISG} = 0, W_{EM} = W_{axle}$$

Battery capacity is defined as the amount of electrical energy that can be drawn from the battery. This parameter is expressed in ampere-hours (Ah).

Table 1 Main parameters for different variables

<i>Variables</i>	<i>Descriptions</i>	<i>Values</i>
P_{ICE}	The ICE maximum power	137 kW
T_{ICE}	The ICE maximum torque	650 Nm
P_{ISG}	The ISG motor maximum power	42 kW
T_{ISG}	The ISG motor maximum torque	400 Nm
P_{EM}	The EM maximum power	144 kW
T_{EM}	The EM maximum torque	1650 Nm
C_{Ro}	The roll resistance	0.015
R_{WH}	Wheels diameter	0.464 m
C_d	Drag coefficient	0.65
Q_{Batt}	Battery capacity	75 Ah

The specific power is also one of the most important parameters of the battery. It is the amount of power per unit mass of the battery (W/kg). The equation of the battery specific power is (Rosario, 2007):

$$P_{spc} = P_{disch} \div M_{batt} \quad (4)$$

where P_{disch} is the discharge power of the battery and M_{batt} is the total battery mass. The corresponding battery power equation is (Wu et al., 2017):

$$P_{batt} / \mu = P_{ISG} + P_{EM} \quad (5)$$

P_{ISG} , P_{EM} , and P_{Batt} are the powers of the ISG motor, electric motors, and battery, respectively. While μ is the charging and discharging efficiency of the battery. These equations determine the relationships between the inputs and outputs of the sub-models that make up the power train layer.

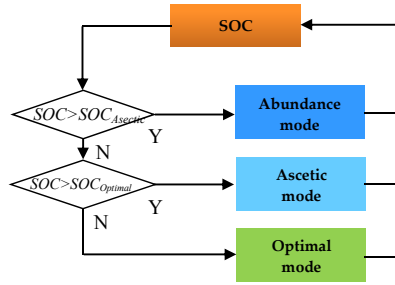
4 Rule-based energy management strategy

In this approach, the vehicle is driven solely by the electric motors during the abundance mode, and the energy used is from the battery packs charged by the ISG motor.

During the ascetic mode, the power drawn from electric traction motors and ICE for PSHEV is exploited, and the battery pack's SOC will be consumed in a descending manner until the vehicle stops.

While in optimal mode, the vehicle relies on ICE power, and the battery pack's SOC remains in its current state until the vehicle stops. Figure 3 illustrates the conditions and triggers for the transition between energy consumption modes, with the value of $SOC_{Ascetic}$ determining the switch from abundance mode to ascetic mode and the value of $SOC_{Optimal}$ determining the transition from an ascetic mode to optimal mode.

Figure 3 Switching power consumption modes (see online version for colours)



4.1 Abundance mode

This is an abundance mode in which the vehicle can rely on the power of high-energy batteries. We have previously explained that the types of movement compatible with this mode are starting, steady speed, and deceleration. When the SOC exceeds 75%, the PSHEV operates on battery power, and electric motors propel the vehicle.

There are three possible powertrain scenarios: starting, acceleration, and steady speed. When the speed is steady, the ISG can charge the batteries by providing all the energy the vehicle needs by exploiting the ICE's motion to generate electrical energy.

In Algorithm 1, T_d represents the required torque of the drive shaft, T_{ICE} represents the output torque of the ICE, and S_{ICE} represents the ICE working condition (i.e., $S_{ICE} = 0$ means the ICE is off, and $S_{ICE} = 1$ means the ICE is starting), and S_{Brk} represents the clutch working condition.

Algorithm 1: Abundance mode

Input: SOC, T_d

Output: T_{ICE} , T_{EM} , T_{ISG} , S_{EM} , S_{Brk}

While SOC $\geq$ 0.75 **do**

read T_d ;

$T_{ICE} \leftarrow 0$; $T_{ISG} \leftarrow 0$;

$S_{ICE} \leftarrow 0$; $S_{Brk} \leftarrow 1$;

if $T_d \geq 0$ **than**

$T_{EM} \leftarrow T_d$;

else

$T_{EM} \leftarrow 0$;

End.

4.2 Ascetic mode

In this mode, the energy level of the batteries is maintained through the use of the ICE alone, with the ISG charging the batteries by generating energy from converting the motion of the ICE into electrical energy.

The PSHEV operates in the ascetic mode when $25\% < \text{SOC} < 75\%$. In this mode, the ISG motor is turned off to avoid losses in efficiency due to the over speed of the ICE.

The PSHEV is driven only by electric motors when it is moving at a low speed or when the T_d is below the minimum operating range of the motors if the speed is high. When T_d is within the ideal operating range of the motors, the PSHEV is driven solely by the motor. If the desired torque exceeds the upper limit of the motors' operating range, ICE and electric motors work together to meet T_d .

Algorithm 2 outlines how the drive control strategy works in this situation. In the algorithm, $T_{ICE_opt_min}/T_{ICE_opt_max}$ represents the lower/upper limits of the ICE's optimal working range, and $n_{Brk_engage_Asc}$ represents the clutch engagement speed threshold in the ascetic mode.

Algorithm 2: Ascetic mode

Input: SOC, T_d , $n_{Brk_engage_Asc}$, $T_{ICE_opt_min}$, $T_{ICE_opt_max}$

Output: T_{ICE} , T_{EM} , T_{ISG} , S_{ICE} , S_{Brk}

```

While  $0.25 \leq \text{SOC} \leq 0.75$  do
  read  $T_d$ ;
  read  $n_{EM}$ ;
  if  $n_{EM} \geq n_{Brk\_engage\_Asc}$  than
    if  $T_d \geq T_{ICE\_opt\_min}$  than
       $S_{ICE} \leftarrow 1$ ;  $S_{Brk} \leftarrow 0$ ;
      if  $T_d > T_{ICE\_opt\_max}$  than
         $T_{ICE} \leftarrow T_{ICE\_opt\_max}$ ;
         $T_{ISG} \leftarrow 0$ ;
         $T_{EM} \leftarrow T_d - T_{ICE}$ ;
      else
         $T_{ICE} \leftarrow T_d$ ;
         $T_{ISG} \leftarrow 0$ ;
         $T_{EM} \leftarrow 0$ ;
    else
       $S_{ICE} \leftarrow 0$ ;  $T_{ICE} \leftarrow 0$ ;
       $S_{Brk} \leftarrow 1$ ;  $T_{ISG} \leftarrow 0$ ;
       $T_{EM} \leftarrow T_d$ ;
  End.

```

Below we will discuss the optimal mode, which is most suitable with the requirement to provide the largest amount of electrical energy to ensure the longest possible driving cycles.

4.3 Optimal mode

In this mode, the ICE provides the majority of the desired torque. The ISG motor adjusts the ICE's torque output to ensure it operates within its ideal working range, and the SOC remains stable at around 25%.

Algorithm 3: Optimal mode

Input: SOC, SOC_{ICE_on} , T_d , $n_{Brk_engage-Asc}$, $T_{ICE_opt_min}$, $T_{ICE_opt_max}$, T_{ICE_min} , T_{ICE_opt} , T_{ICE_max}
Output: T_{ICE} , T_E , T_{ISG} , S_{ICE} , S_{Brk}

Put SOC = 0.25;

read T_d ;

read n_{EM} ;

if $n_{EM} \geq n_{Brk_engage-Asc}$ **than**
 $S_{ICE} \leftarrow 1$; $S_{Brk} \leftarrow 0$;

if $T_d > T_{ICE_min}$ **than**
if $T_d > T_{ICE_max}$ **than**
 $T_{ICE} \leftarrow T_{ICE_opt_max}$;

 $T_{ISG} \leftarrow 0$; $T_{EM} \leftarrow T_d - T_{ICE}$;

else
 $T_{ICE} \leftarrow T_d$;

 $T_{ISG} \leftarrow 0$; $T_{EM} \leftarrow 0$;

else
 $T_{ICE} \leftarrow T_{ICE_opt_min}$;

 $T_{EM} \leftarrow 0$;

 $T_{ISG} \leftarrow T_d - T_{ICE}$;

else
 $S_{Brk} \leftarrow 1$;

if SOC $\leq SOC_{ICE_on}$ **than**
 $S_{ICE} \leftarrow 1$; $T_{ICE} \leftarrow T_{ICE_opt}$;

 $T_{EM} \leftarrow T_d$; $T_{ISG} \leftarrow -T_{ICE}$;

else
 $S_{ICE} \leftarrow 0$; $T_{ISG} \leftarrow 0$;

 $T_{ICE} \leftarrow 0$; $T_{ICE} \leftarrow T_d$;

End.

At low speeds, the clutch disengages, and the traction motors power the PSHEV. Conversely, when the SOC is higher than SOC_{ICE_on} , the PSHEV operates in series mode. T_{ICE_opt} represents the ICE's output torque for efficient production by the ISG motor, and $n_{Brk_engage_opt}$ is the speed threshold for clutch engagement in optimal mode.

At high speeds, the clutch is engaged, and if the value of T_d falls below $T_{ICE_opt_min}$, the ICE operates at the lower limit of its optimal working range, and the torque is utilised in the ISG motor's power generation process.

When T_d falls within the ICE's optimal working range, the PSHEV is driven by the ICE alone, but if T_d exceeds $T_{ICE_opt_max}$, the ICE operates at its higher limit and is assisted by electric motors to meet the required torque.

5 Modelling and implementation

5.1 The DEVS formalism

DEVS is a formalism that represents the formal structure of a model. In the DEVS formalism, mathematical models define events that occur at different times. The DEVS formalism uses two models: the atomic (behavioural) model and the coupled (structural) model. The atomic model is the core component of DEVS modelling, and it is defined by a set of states and the transitions between them (Capocchi, 2014). The formal specification of an atomic DEVS model is as follows (Capocchi et al., 2006):

$$AM = (X, Y, S, \delta_{ext}, \delta_{int}, \lambda, ta) \text{ in which:}$$

- X represents the set of inputs
- S represents the set of states
- Y represents the set of outputs
- $\delta_{int} : S \rightarrow S$ represents the internal transition function;
- $\delta_{ext} : Q \times X \rightarrow S$ represents the external transition function, in which:
- $\lambda : S \rightarrow Y$ represents the output function;
- $ta : S \rightarrow R + 0, \infty$ represents the time advance function;
- $Q = \{(s, e) \mid s \in S, 0 \leq e \leq ta(s)\}$ represents the total state set and e is the duration of the last transition.

The DEVS formalism uses the notion of description hierarchy, which allows the construction of so-called ‘coupled’ models by combining a set of sub models and three coupling relationships with these sub models. A coupled model is created from two or more models, which can be atomic or even other coupled models. The crux of the matter is to direct incoming, outgoing, and internal events to the right places. In classic DEVS formalism with port, the specifications of a coupled model are as follows [35]:

$$CM = (X, Y, D, \{Md \mid d \in D\}, EIC, EOC, IC)$$

in which:

- $X = \{(p, v) \mid p \in IPorts, v \in Xp\}$ represents the set of input ports and values
- $Y = \{(p, v) \mid p \in OPorts, v \in Yp\}$ represents the set of output ports and values
- D represents the set of the component names
- $Md = (Xd, Yd, S, \delta_{ext}, \delta_{int}, \lambda, ta)$ represents a DEVS basic atomic model with:

- $Xd = \{(p, v) \mid p \in IPortsd, v \in Xp\}$ and
- $Yd = \{(p, v) \mid p \in OPortsd, v \in Yp\}$
- External input coupling (EIC), between external inputs and component inputs:

$$EIC \subseteq \{ ((CM, ipCM), (d, ipd)) \mid ipCM \in IPorts, d \in D, ipd \in IPortsd \}$$

- External output coupling (EOC), between external outputs and component outputs:

$$EOC \subseteq \{ ((d, opd), (CM, opCM)) \mid opCM \in OPorts, d \in D, opd \in OPortsd \}$$

- Internal coupling (IC), between component outputs and component inputs:

$$IC \subseteq \{ (a, opa), (b, ipd) \mid a, b \in D, opa \in Oports, pb \in IPortsb \}.$$

5.2 DEVS modelling

In this subsection, the combined energy management system of PSHEVs is described through their coupled models and their atomic components. The aim is to formally model it using the DEVS formalism in preparation for simulation.

The proposed system consists of two subsystems: the Powertrain layer subsystem and the Control layer subsystem. This paper explains the workings of the control layer subsystem, which is critical in implementing rule-based energy consumption optimisation for the vehicle. Although the method for describing atomic models is consistent across all models, this subsection will only describe the control layer coupled model and its atomic components. The two-layered control model comprises two atomic models: the speed controller model and the EM strategy model. The following is the structure of the DEVS coupled model for the control layer:

$$Control_layer = (X, Y, D, \{M_d \mid d \in D\}, EIC, EOC, IC)$$

in which:

- $X = \{ (p, v) \mid p \in IPorts, v \in Xp \}$ represent the inputs;
- $Y = \{ (p, v) \mid p \in OPorts, v \in Yp \}$ represent the outputs;
- D represents the set of names of the atomic or coupled models that compose the Control_layer;
- $D = \{Speed\ Controller, EMS\ Strategy\}$;
- M_d represent the set of atomic or coupled models that compose the Control_layer;
- $M_{Speed\ Controller}$ represents the model of Speed Controller subsystem
- $M_{EM\ Strategy}$ is the model of EM Strategy subsystem
- $EIC = \{ ((Control_Layer, a), (d, b)) \mid a \in IPortsS, b \in IPorts d \}$
- $EOC = \{ ((d, b), (Control_Layer, a)) \mid a \in OPorts\ of\ Control_Layer, b \in OPorts d \}$;
- $IC = \{ ((i, a), (j, b)) \mid i, j \in D, i, j, a \in OPorts i, b \in IPorts j \}.$

The EIC connects the ports of the control layer model to the ports of the component models, from which external events originate. The EOC connects the ports of the control layer model to the ports of the sub models that produce output events, and the IC connects the sub models. In the following sections, the speed controller atomic model and the EM strategy atomic model is described.

5.2.1 The 'speed controller' sub-model

In order for the vehicle to be set in the three modes, economic, abundant or optimal, the vehicle's speed must be controlled in line with the charge level of its batteries. The vehicle speed can be set through the speed controller sub-system. In this case, the vehicle speed is calculated as a percentage.

Figure 4 shows the DEVS atomic model of the Speed Controller sub-system. This model changes to the state of Starting, Turn off, Off try, Braking, Acceleration and Deceleration. In each case, the state of speed is different, either increasing, decreasing, or equal to 00 and so on. Which means that the model will only be in one of these states at any time. The Speed Controller sub-model has three inputs: $\{SC, DSV, COO\}$, where:

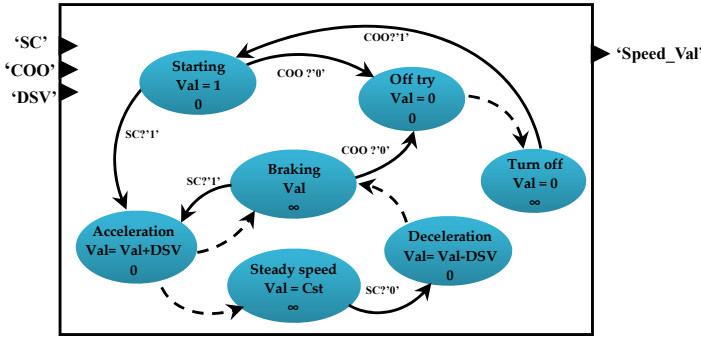
SC : Speed Control, accelerate or decelerate the vehicle speed. $SC = \{0, 1\}$, the event $SC?'0'$ means decelerate the vehicle speed; the event $SC?'1'$ means accelerate.

DSV : Desired Speed Value; Absolute value of desired speed value. $DSV \in [0, 100]$.

COO : Go to off or on. $COO?'0'$ means go to 'Off'.

$COO?'1'$ means go to 'On'. Thus, the vehicle speed can change from 0 to 100% or from 100 to 0%.

Figure 4 'Speed controller' atomic model (see online version for colours)



We give the formal specification of DEVS 'Speed Controller' atomic model as follows:

$SpeedController = (X, Y, S, \delta_{ext}, \delta_{int}, \lambda, ta)$ in which:

- $X = \{COO, DSV, SC\}$, represents the input event variables
- $Y = \{Off, Low, Medium, Hight, Max\}$
- State variables: $S = \{(phase, val, ta)\}$ in which
 - $Phase = \{Starting, Offtry, Turnoff, Braking, Acceleration, Steadyspeed, Deceleration\}$;
 - $Val \in [0, 100]$ represents the current speed level.

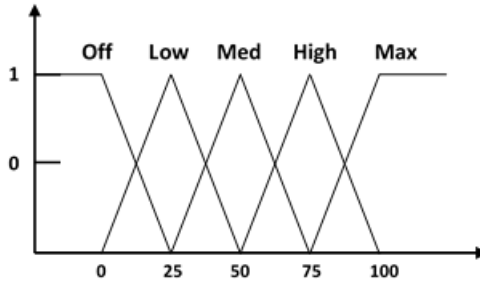
- $\delta_{\text{ext}}(\text{Turn off}, \text{COO?'1'}) = (\text{Starting}, \text{Val} = 1, 0),$
 $\delta_{\text{ext}}(\text{Starting}, \text{COO?'0'}) = (\text{Off try}, \text{Val} = 0, 0),$
 $\delta_{\text{ext}}(\text{Starting}, \text{SC?'1'}) = (\text{Acceleration}, \text{Val} = \text{Val} + \text{DSV}, 0)$
 $\delta_{\text{ext}}(\text{Braking}, \text{SC?'1'}) = (\text{Acceleration}, \text{Val} = \text{Val} + \text{DSV}, 0)$
 $\delta_{\text{ext}}(\text{Braking}, \text{COO?'0'}) = (\text{Off try}, \text{Val} = 0, 0),$
 $\delta_{\text{ext}}(\text{Steady speed}, \text{SC?'0'}) = (\text{Deceleration}, \text{Val} = \text{Val} - \text{DSV}, 0);$
- $\delta_{\text{int}}(\text{Acceleration}) = \text{Steady speed}, \delta_{\text{int}}(\text{Off try}) = \text{Turn off},$
 $\delta_{\text{int}}(\text{Deceleration}) = \text{Braking}, \delta_{\text{int}}(\text{Acceleration}) = \text{Braking};$
- $\lambda(\text{Starting}) = \mu(\text{Val}), \lambda(\text{Acceleration}) = \mu(\text{Val}), \lambda(\text{Deceleration}) = \mu(\text{Val}),$
 $\lambda(\text{Off try}) = \mu(\text{Val}).$

λ represents output functions, in which μ is the membership function (MF¹) of this atomic model (Figure 5).

- $\text{ta}(\text{Turn off}) = \infty, \text{ta}(\text{Starting}) = 0, \text{ta}(\text{Off try}) = 0, \text{ta}(\text{Braking}) = \infty,$
 $\text{ta}(\text{Acceleration}) = 0, \text{ta}(\text{Steady speed}) = \infty, \text{ta}(\text{Deceleration}) = 0.$

Initially, the initial state of this model is OFF (before the vehicle is powered on), which is a negative state since its lifetime is ∞ . When is the event COO?'1' coming, the transition to the ON state (Vehicle start-up) occurs thanks to the external transition function. The access state 'starting' of this transition is a temporary state since it has a default lifetime of 0: its role is to change the value of the variable 'Val' to 1.

Figure 5 MF associated with 'speed controller' atomic model



The next internal transition brings us to a new negative state, called 'Braking', which maintains the value of the variable "Val". During this, the model receives an external signal via the event SC?'1', to switch to the "acceleration" state; which leads to an increase in the speed of the vehicle (i.e., It increments the value of the variable Val to Val + DSV, where DSV is the desired speed value).

The next internal transition can lead to a 'steady speed' state. The event SC?'0' leads to a 'deceleration' state, which leads to a decrease in the speed of the vehicle (i.e., It

decrements the value of the variable *Val* to $Val - DSV$). The event $COO?'0'$ leads to a 'Off try' state which commands to stop the vehicle.

The subsequent internal transition of the model inevitably leads to a return to its initial state. If the external event $COO?'0'$ comes and the model is in the 'Starting' state, it will go to the 'Off try' state and then, it can also return to the initial state. The output function gives us what is called 'Speed_Val'.

Due to the possibility of some ambiguity in the value of the resulting speed due to its permanent change during the vehicle's movement, we convert the 'Val' variable to a MF linguistic variable that changes from 0 to 1 with fixed values in order to cover the potential information shortage.

5.2.2 The 'EM strategy' sub-model

This part focuses on the EM strategy sub model, which plays a crucial role in enhancing the energy management of PSHEVs. This component implements the actual adjustment of the power consumption mode of the PSHEV based on the energy management plan received from the speed controller sub system.

Figure 6 shows the atomic DEVS model of the EM Strategy sub-system that can take the following states: Optimal, towards_Ascetic, Ascetic, towards_Abundance and Abundance. The EM Strategy sub-model has two inputs: 'EM_Plan' and 'Step'. The EM_Plan variable can take two binary values, '0' or '1'; A value of '0' indicates going to Abundance, a value of '1' indicates going to Ascetic. This form can take the state of "Abundance", "Ascetic", or "Optimal". We give the formal specification of DEVS 'EM Strategy' atomic model as follows:

$$EMStrategy = (X, Y, S, \delta_{ext}, \delta_{int}, \lambda, ta)$$

in which:

- $X = \{EM_Plan, Step\}$ presents the set of input event variables, with:

$EM_Plan = \{0, 1\}$, through this port, the model triggers the policy of energy use:

The external event $EM_Plan?'1'$ means adjust towards Abundance mode; the external event $EM_Plan?'0'$ means adjust towards Ascetic mode.

'Step' is a value of adjustment, $Step \in [0, 1]$.

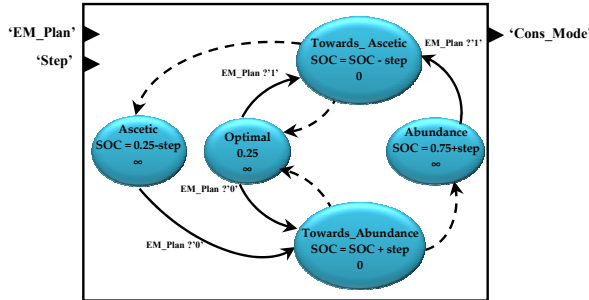
- $Y = \{ASCETIC, OPTIMAL, ABUNDANCE\}$;
- State variables: $S = \{(phase, SOC, ta)\}$, where:
 - $Phase = \{Abundance, Optimal, Ascetic, towards_Abundance, towards_Ascetic\}$;

The variable 'SOC' represents the SOC of the batteries corresponding to each mode,, ranging from 0 to 1, where when (≤ 0.25) indicates 'Ascetic mode', 0.25 indicates 'Optimal mode' and when (≥ 0.75) indicates 'Abundance mode', $SOC \in [0, 1]$;

- The output function of this model λ with: $Y = I(m)$
- $\delta_{ext}(Optimal, EM_Plan = '1') = (towards_Ascetic, SOC = SOC - step, 0)$,
 $\delta_{ext}(Optimal, EM_Plan = '0') = (towards_Abundance, SOC = SOC + step, 0)$,
 $\delta_{ext}(Abundance, EM_Plan = '1') = (towards_Ascetic, SOC = SOC - step, 0)$
- $\delta_{int}(towards_Abundance) = Optimal$, $\delta_{int}(towards_Ascetic) = Optimal$,
 $\delta_{int}(towards_Ascetic) = Ascetic$ if $m \leq 0.25$,
 $\delta_{int}(towards_Abundance) = Abundance$ if $SOC \geq 0.75$
- $\lambda(towards_Ascetic) = ASCETIC$ if $SOC \leq 0.25$, $\lambda(towards_Ascetic) = OPTIMAL$,
 $\lambda(towards_Abundance) = OPTIMAL$,
 $\lambda(towards_Abundance) = ABUNDANCE$ if $SOC \geq 0.75$
- $ta(towards_Abundance) = 0$, $ta(towards_Ascetic) = 0$, $ta(Optimal) = \infty$,
 $ta(Ascetic) = \infty$, $ta(Abundance) = \infty$.

In this work it is assumed that the initial state is 'Abundance' with $SOC \geq 0.75$. The external event $EM_Plan = '1'$ occurs transition to the 'Towards_Ascetic' state when the 'step' reduces the SOC value to less than 0.75. The new state 'Toward_Ascetic' for this transition is a temporary state as it has a default lifetime of 0: It updates the vehicle's consumption mode to become the ascetic mode. (In fact, the variable 'SOC', which was >0.25 , changes its value to $SOC - step$ to be ≤ 0.25).

Figure 6 'EM strategy' atomic model (see online version for colours)



If $SOC \leq 0.25$, the next internal transition leads to entering ascetic mode. We get to a new state called 'Ascetic'. The "ascetic" state is negative i.e., its lifetime is ∞ : it only saves the consumption mode of PSHEV. When the external event $EM_Plan = '0'$ arrives; we go to the 'Toward_Abundance' state. The arrival state 'Toward_Abundance' is also transitory. Its role is to increase the level value of the batteries when the batteries are charged, and the SOC variable value rises to the $SOC + step$. The next internal transition allows the transition to the 'optimal' state when SOC reaches 0.25, if $SOC \geq 0.75$. From that, it is possible to return to the initial state of 'Abundance' through the internal transition of the form.

5.3 *Simulation of the proposed model using the JDEVS tool*

We have commenced installing and commissioning our coupled and atomic models using the DEVSimPy modelling and simulation environment. DEVSimPy (Capocchi et al., 2011), is a tool that enables the specification of DEVS models through Python code. The overall model encompasses two coupled models: the powertrain layer and the control layer.

The powertrain layer coupled model includes ten atomic models: the ICE, Clutch, ISG, Gear Box, PW Converter, Transmission, Motors, Batteries, and two wheel models. The control layer coupled model encompasses two atomic models: a speed controller and an energy management strategy.

In the powertrain layer, the atomic model ICE includes one input, which is *Tice_req*, and it represents the required ICE torque; it also includes one output, which is *Tice*, and it represents the output ICE torque. The atomic model Clutch includes one input, which is *Tice*, and it represents the ICE torque; it also includes one output, which is *T_mech*, and it represents the mechanical torque. The atomic model ISG includes one input, which is *Tice*, and it represents the ICE torque; it also includes one output, which is *I_inv*, and it represents the inverted intensity. The atomic model Gear Box includes one input, which is *T_mech*, and it represents the mechanical torque; it also includes one output, which is *T_drv*, and it represents the torque of driving.

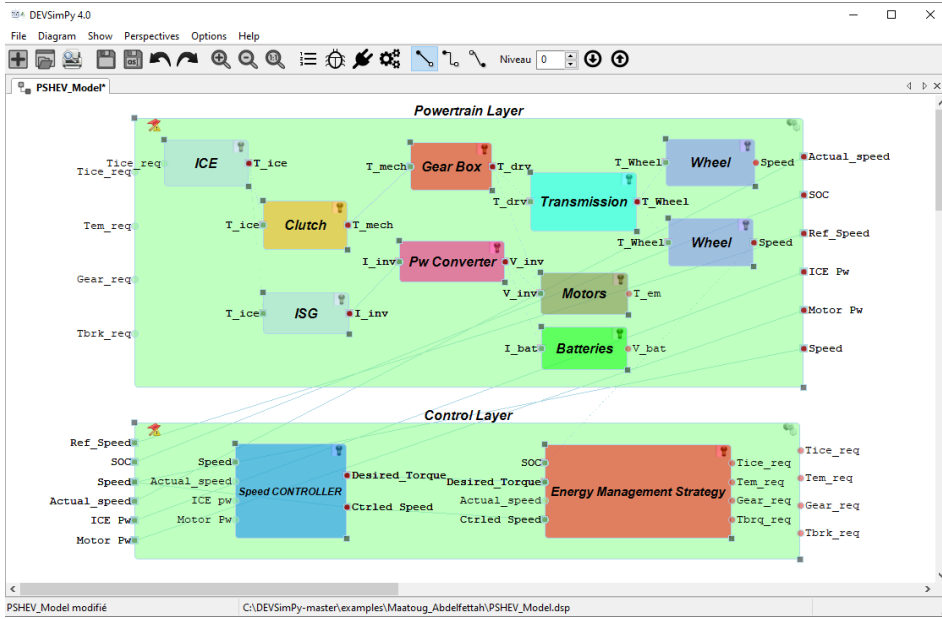
The atomic model PW Converter includes one input, which is *I_inv*, and it represents the inverted intensity; it also includes one output, which is *V_inv*, and it represents the the inverted electrical voltage. The atomic model Transmission includes one input, which is *T_drv*, and it represents the torque of driving; it also includes one output, which is *T_wheel*, and it represents the torque applied to the wheels. The atomic model Motors includes one input, which is *V_inv*; it also includes one output, which is *T_em*, and it represents the torque of electric motors. The Batteries atomic model has one entry, *I_bat*, which represents the density of the batteries; It also includes one output which is *V_bat*, representing the batteries voltage. And the atomic model Wheel includes one input, which is *T_wheel*; it also includes one output, which is *Speed*, and it represents the resulting speed of the vehicle.

In the control layer, The atomic model Speed Controller includes four inputs, which are *Speed*, *Actual_speed*, *ICE pw* and *Motor pw*; and it represents the expected speed and the actual speed of the vehicle, power of ICE and of motors; it also includes two outputs, which are *Desired_Torque* and *Ctrlled Speed*, and it represents the desired torque and the resulting speed after control.

And the atomic model Energy Management Strategy in-cludes four inputs, which are *SOC*, *Desired_Torque*, *Actual_speed* and *Contrled Speed*; when *SOC* represents the SOC of batteries; it also includes four outputs, which are *Tice_req*, *Tem_req*, *Gear_req* and *Tbrk_req*; and it represents the required torque of ICE and electric motors, the required gear and the rquired torque under braking.

In Figure 7, the inputs and outputs of each model determine the relationships between the models when they are connected to each other. The atomic DEVS models are promptly transformed into Python instructions during implementation. During the model generation phase, the DEVSimPy interface automatically generates the model's code skeleton in Python.

Figure 7 Representation of the global model with the DEVSimPy tool (see online version for colours)



When adding an empty atomic component and defining its input and output interfaces, the external output and transition functions create new event vectors, which are then consolidated into a global event list.

The programming objective is to define the dynamics of atomic models using their methods. Each atomic model will be saved simultaneously in the library to build the desired coupled model. The DEVSimPy simulator offers a convenient feature, allowing us to add or remove any model, either atomic or coupled, for smooth improvement (Capocchi et al., 2011). This feature played a crucial role in the choice of this simulator for the work.

Furthermore, the simulation of the models can be done directly from a graphical interface, allowing us to observe the generated model's behaviour and adjust its parameters or correct any errors. Additionally, the experiment-executing applications are located within the same modelling interface.

6 Experimental results and discussions

The objective of validation is to confirm that the system operates as intended in real life scenarios by varying conditions and running simulations (Zeigler et al., 2000). The problem is described in detail in Sections 3 and 4, and in this section, the performance of our proposal is assessed through simulations and discussion of the results obtained.

To showcase the potential of this rule-based optimisation, a strategy that carefully demonstrates its efficacy needs to be considered. Therefore, the key factors that significantly impact the design of the scene and the main components are highlighted, including the power consumption modes and levels of the different parts, such as the

batteries and electric or diesel motors, and the source of power and torque, whether electric or diesel. We simulated the model several times, and changes were made based on the simulation results to enhance its performance. The best results obtained from the most optimised model are summarised in the following subsections:

6.1 Hybrid system simulations

In this work it is assumed that traffic lines operate on a fixed schedule. Each simulated ride lasts 8 h, with the vehicle moving from end to end every 30 min. The routes travelled by vehicles involve various transportation links. In general, the first three links are usually crowded. The other links have smoother traffic.

The simulations will be run to see what happens in different driving cycles. Traffic information such as speed, flow, and density for the eight links will be recorded per second on all eight links. The collected traffic information will also be used to improve our proposed system.

In total, the driving cycle covers a distance of 6 km and lasts 1440 s. Figure 8 depicts changes in speed as a function of time. The figure shows that speed is mainly constant during most periods, reaching approximately 90 km/h. The results obtained are hypothetical modifications of our model. To demonstrate the power distribution among different parts of the vehicle, the baseline SOC and final SOC are set at 0.7 and 0.35, respectively, ensuring sufficient battery capacity to perform the eight consecutive driving cycles. Table 2 presents the output power consumption values for the various motors.

Figure 8 Variation of speed in the driving cycle (see online version for colours)

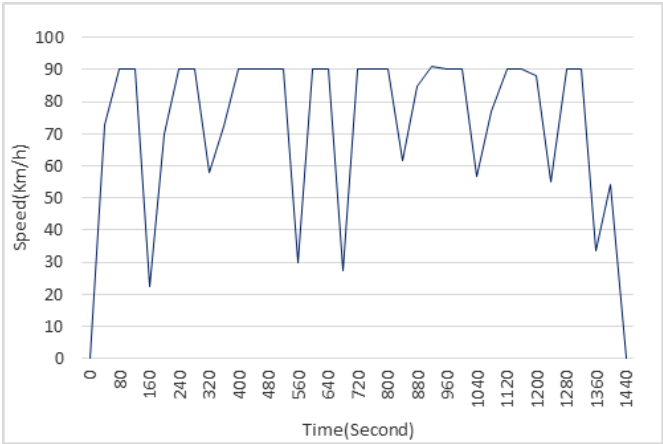


Table 2 Settings and simulation results

<i>Parameters</i>	<i>Result values</i>
Initial SOC	0.7
Terminal SOC	0.35
Number of driving cycles	08
Motors consumption	7237 Wh/100 km
ICE consumption	16.18 L/100 km

6.2 Power distribution between the various parts of the vehicle

The simulations in Figure 9 show the power distribution among different vehicle parts. The motor is set to rotate between 85 rad/sec and 90 rad/sec, and the default value at peak load is equivalent to 800 rpm. The vehicle can be in four distinct states: acceleration, deceleration, steady speed, and stopping.

Figure 9 The power in different motors and the corresponding SOC and speed (see online version for colours)

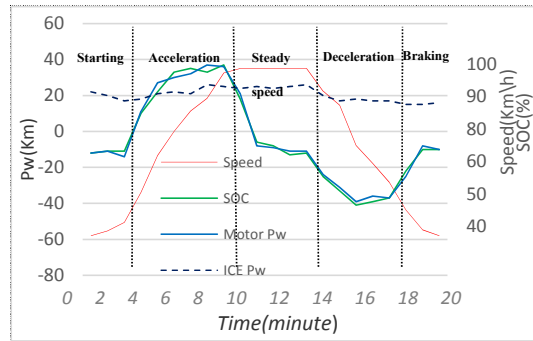


Figure 9 provides an overview of the power (kW) vs. time (t) of the motors, the charge ratio of one battery among five batteries, and ICE for the different states of acceleration, deceleration, steady speed, braking and stopping. The vehicle utilises energy stored in the battery, and this simulation assumes that the battery is precharged.

However, to develop hybrid vehicles with reduced emissions, renewable energy sources can be integrated into the system. By observing the curves, when the vehicle is stationary or travelling at a steady speed, most of the power comes from the ICE, with a minor contribution from the electric motors. In this case, the battery is charged through the rotation of the ICE. During deceleration, the power used primarily comes from electric motors relying on battery power.

Under acceleration, both the ICE and electric motors are utilised for propulsion. In this way, energy is conserved as the batteries are charged most of the time especially since the vehicle is at a steady speed most of the time. This contributes to environmental preservation by reducing the use of ICE.

6.3 Torque comparison of various motors

This experiment examines the applied torque of both the electric motor and ICE in the various states of the vehicle. These are the actual stages included in the movement cycle in this simulation.

Table 3 provides a detailed overview of all these stages, from the beginning to the end of the simulation. A complete transmission entails changes in the conditions of components across the power train and gearbox, including the motors, ICE, and clutch.

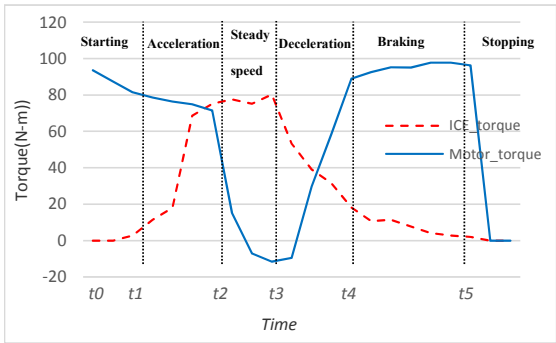
The driving force, the torque value, and the transmission sources, either from electric motors, ICE, or both, determine the state of the vehicle's movement, whether it is stopping, accelerating, at a steady speed, or decelerating.

Table 3 Sources of torque in various cases of the vehicle

<i>Time</i>	<i>Transmission tool</i>	<i>Operating state</i>
$t_0 - t_1$	Motors torque is mostly used	Starting
$t_1 - t_2$	Motors and ICE torques are used	Acceleration
$t_2 - t_3$	ICE torque is mostly used	Steady speed
$t_3 - t_4$	Motors torque is used	Declaration
$t_4 - t_5$	Motors torque is mostly used	Braking
$t_5 -$	No torque is used	Stopping

Figure 10 provides a more in-depth analysis of the torque wrenching process. Upon determining the stages of the different conditions of the vehicle and examining the torque values used, whether electric or ICE torque, during each stage, we find them to be accurate and reasonable.

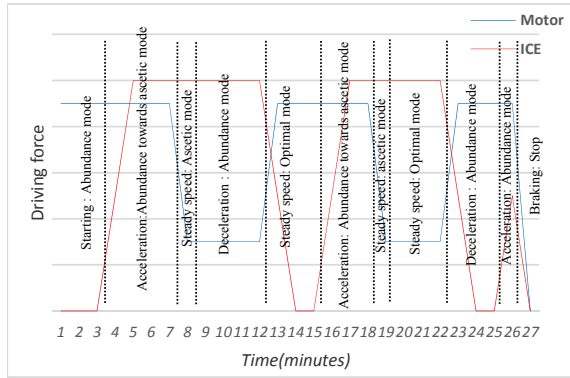
Figure 10 Torques comparison (see online version for colours)



6.4 Observation of the energy consumption modes adopted during the simulation

Next, we will examine a single driving cycle and analyse its energy consumption patterns. The scenario depicted in the figure encompasses the following steps: starting, acceleration, steady speed, deceleration, acceleration, steady speed, and finally, stopping.

At each stage, the energy consumption mode employed is documented and assessed, along with the effectiveness of our proposed model in enhancing the vehicle's energy efficiency. Figure 11 shows that the most frequently adopted modes are ascetic or optimal. In these two modes, the batteries are charged, reducing the extent to which the battery level drops. This results in significant energy savings, regardless of the level of use of the electric motors, which is the ultimate objective.

Figure 11 Sources of force in the different modes (see online version for colours)

7 Conclusion and future works

This study proposes a new rule-based method for calibrating the energy consumption control strategy of HEVs. The controller aims to determine the optimal power train behaviour of the PSHEV system during different driving cycles. An optimisation-based calibration procedure is introduced to obtain more feasible control actions for PSHEVs by modelling the system using the DEVS formalism and making it accessible.

Experiments show that the operating range of the electric motors has been increased, the electric motors and the ICE can be used together, and the PSHEV operates in electric-only mode for more extended periods, diesel consumption is reduced, and the batteries are charged in most situations. If we compare our vehicle to which we apply the optimisation algorithms to vehicles that do not apply our approach, we gain about 15.25% additional batteries charge and reduce the batteries power consumption to more than 11%. The proposed rule-based optimisation approach effectively improves the energy management strategies currently used by PSHEV manufacturers, especially in static mode driving scenarios.

In the future, a multi-energy system is envisioned that not only relies on charging the battery at electric vehicle charging stations but also utilises renewable energy sources such as solar panels and wind turbines for continuous battery recharging. Also, our PSHEV will be actually modelled on reality using all the necessary devices and motors, where we install the same control system proposed in our paper on it and then compare the results of this work by measuring all the results in different driving cycles and comparing them with the results obtained with another vehicle that does not use this system and with the results obtained through simulation. In terms of modelling and simulation, alternative methods such as Parallel DEVS (Zeigler and Sarjoughian, 2003), Cell-DEVS (Wainer, 2002), DSDEVS (Nutaro, 2011), or G-DEVS (Zacharewicz, 2006), which are extensions of the DEVS formalism, may be used to better represent the system. A good number of them constitute lightweight libraries that can be considered as frameworks. On the other hand, DEVSImPy is a graphical modelling, experimentation and debugging environment that uses PythonPDEVS as the simulation core. However, most of these tools are based on a jointly developed simulator (Franceschini, 2017).

Finally, it is worth noting that the ability to capture the general model and improve it through repeated experiments and necessary corrections is the most significant contribution of this work.

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References

- Adnan, N., Nordin, S.M., Rahman, I., Vasant, P. and Noor, M.A. (2018) ‘An overview of electric vehicle technology: a vision towards sustainable transportation’, *Intelligent Transportation and Planning: Breakthroughs in Research and Practice*, pp.292–309, doi: 10.4018/978-1-5225-5210-9.ch013.
- Ahmed, A., Yelamali, P. and Udayakumar, R. (2020) ‘Modelling and simulation of hybrid technology in vehicles’, *Energy Reports*, Vol. 6, pp.589–594, <https://doi.org/10.1016/j.egy.2019.11.123>
- Anbaran, S.A., Idris, N.R.N., Jannati, M., Aziz, M.J. and Alsofyani, I. (2014) ‘Rule-based supervisory control of split-parallel hybrid electric vehicle’, *2014 IEEE Conference on Energy Conversion (CENCON)*, IEEE, October, Johor Bahru, Malaysia, pp.7–12, doi: 10.1109/CENCON.2014.6967468.
- Asfoor, M.S., Sharaf, A.M. and Beyerlein, S. (2014) ‘Use of GT-suite to study performance differences between internal combustion engine (ICE) and hybrid electric vehicle (HEV) powertrains’, *Proceedings of the 16th International Conference on Applied Mechanics and Mechanical Engineering, Military Technical College*, May, Egypt, pp.19–34, doi: 10.21608/AMME.2014.35473.
- Baktayan, A.A., Al-Baltah, I.A. and Abd Ghani, A.A. (2022) ‘Intelligent pricing model for task offloading in unmanned aerial vehicle mounted mobile edge computing for vehicular network’, *Journal of Communications Software and Systems*, Vol. 18, No. 2, pp.111–123, <https://doi.org/10.24138/jcomss-2021-0154>
- Barlas, Y. (1989) ‘Multiple tests for validation of system dynamics type of simulation models’, *European Journal of Operational Research*, Vol. 42, No. 1, pp.59–87, [https://doi.org/10.1016/0377-2217\(89\)90059-3](https://doi.org/10.1016/0377-2217(89)90059-3)
- Capocchi, L. (2014) *DEVSimPy-Version 2.8*, Dissertation, University of Corsica, Laboratory SPE UME CNRS 6134, https://www.academia.edu/23325162/DEVSimPy_Version_2_8
- Capocchi, L., Bernardi, F., Federici, D. and Bisgambiglia, P.A. (2006) ‘BFS-DEVS: a general DEVS-based formalism for behavioral fault simulation’, *Simulation Modelling Practice and Theory*, Vol. 14, No. 7, pp.945–970, <https://doi.org/10.1016/j.simpat.2006.05.002>
- Capocchi, L., Santucci, J.F., Poggi, B. and Nicolai, C. (2011) ‘DEVSimPy: A collaborative python software for modeling and simulation of DEVS systems’, *Proceedings of the IEEE 20th International Workshops on Enabling Technologies: Infrastructure for Col-Laborative Enterprises*, IEEE, Paris, France, pp.170–175, doi: 10.1109/WETICE.2011.31.
- Chung, C.Y., Shepelev, A., Qiu, C., Chu, C.C. and Gadh, R. (2014) ‘Mesh network for RFID and electric vehicle monitoring in smart charging infrastructure’, *Journal of Communications Software and Systems*, Vol. 10, No. 2, pp.114–123, <https://doi.org/10.24138/jcomss.v10i2.132>

- Fan, B.S.M. (2007) *Modeling and Simulation of Hybrid Electric Vehicle Using Matlab/Simulink and ADAMS*, Dissertation, University of Waterloo in Fulfillment of the Thesis Requirement for the Degree of Master of Applied Science in Mechanical Engineering, Waterloo, Canada, <http://hdl.handle.net/10012/3237>
- Franceschini, R.R. (2017) *Approche formelle pour la modélisation et la simulation à événements discrets de systèmes multi-agents*, Dissertation, Université Pascal Paoli, Corte, France.
- Friedrich, G. and Girardin, A. (2009) 'Integrated starter generator', *IEEE Industry Applications Magazine*, Vol. 15, No. 4, pp.26–34, doi: 10.1109/MRA.2009.932592.
- Frijlink, P., Schaerlaeckens, W., van den Tillaart, E. and de Haas, J. (2001) 'Simulation of a vehicle with an ICE, CVT, and ISG power-train-a. pre-study for concept evaluation and dimensioning', *SAE Transactions*, pp.2124–2138.
- Ghorbani, R., Bibeau, E., Zanetel, P. and Karlis, A. (2007) 'Modeling and simulation of a series parallel hybrid electric vehicle using REVS', *2007 American Control Conference*, IEEE, July, New York, NY, USA, pp.4413–4418, doi: 10.1109/ACC.2007.4282828.
- Gupta, V., Sharma, M. and Thakur, N. (2011) 'Mathematical modeling of actively controlled piezo smart structures: a review', *Smart Structures and Systems*, Vol. 8, No. 3, pp.275–302, <https://doi.org/10.12989/sss.2011.8.3.275>
- He, Y., Riosb, J., Chowdhury, M., Pisu, P. and Bhavsar, P. (2012) 'Forward power-train energy management modeling for assessing benefits of integrating predictive traffic data into plug-in-hybrid electric vehicles', *Transport. Res. Part D: Transp. Environ.*, Vol. 17, No. 3, pp.201–207, <https://doi.org/10.1016/j.trd.2011.11.001>
- Huang, Q., Gardoni, P. and Hurlebaus, S. (2015) 'Assessment of modal parameters considering measurement and modeling errors', *Smart Struct Syst*, Vol. 15, No. 3, pp.717–733, <http://dx.doi.org/10.12989/sss.2015.15.3.717>
- Kaleemullah, M. and Faris, W.F. (2022) 'Optimisation of robust and LQR control parameters for discrete car model using genetic algorithm', *International Journal of Vehicle Systems Modelling and Testing*, Vol. 16, No. 1, pp.40–63, <https://doi.org/10.1504/Ijvsmt.2022.126968>
- Lee, E., Kapoor, S., Sikder, T. and He, Y. (2017) 'An optimal robust controller for active trailer differential braking systems of car-trailer combinations', *Int. J. Vehicle Systems Modelling and Testing*, Vol. 12, Nos. 1–2, pp.72–93, <https://doi.org/10.1504/IJVSMT.2017.087957>
- Liu, W. (2013) *Introduction to Hybrid Vehicle System Modeling and Control*, 2nd ed., John Wiley & Sons Inc., Canada.
- Ma, Y., Shi, D., Song, J. and Zuo, S. (2022) 'Review on energy management strategies of PHEV', *Highlights in Science, Engineering and Technology*, Vol. 3, pp.144–157, <https://doi.org/10.54097/hset.v3i.703>
- Maatoug, A. and Belalem, G. (2014) 'Conception and validation of smart building energy management system BEMS using the discrete event system specification DEVS', *Journal of Communications Software and Systems*, Vol. 10, No. 2, pp.107–113, <https://hrcak.srce.hr/180035>
- Maatoug, A., Belalem, G. and Mahmoudi, S. (2023) 'A location-based fog computing optimization of energy management in smart buildings: DEVS modeling and design of connected objects', *Frontiers of Computer Science*, Vol. 17, No. 2, pp.1–17, <https://doi.org/10.1007/s11704-021-0375-z>
- Murphey, Y.L., Jungme, P., Zhihang, C., Kuang, M.L., Masrur, M.A. and Phillips, A.M. (2013) 'Intelligent hybrid vehicle power control'— part II: online intelligent energy management', *IEEE Trans. Veh. Technol.*, Vol. 62, No. 1, pp.69–79, doi: 10.1109/TVT.2012.2217362.
- Negadi, K., Boudiaf, M., Araria, R. and Hadji, L. (2022) 'Improvement of the amplification gain for a propulsion drives of an electric vehicle with sensor voltage and mechanical speed control', *Smart Structures and Systems*, Vol. 29, No. 5, pp.661–675, <https://doi.org/10.12989/sss.2022.29.5.661>
- Nutaro, J. (2011) *Building Software for Simulation: Theory and Algorithms, with Applications in C++*, John Wiley & Sons, Amazon France, doi: 10.1002/9780470877999.

- Peng, J., He, H. and Xiong, R. (2017) 'Rule based energy management strategy for a series-parallel plug-in hybrid electric bus optimized by dynamic programming', *Applied Energy*, Vol. 185, pp.1633–1643, <https://doi.org/10.1016/j.apenergy.2015.12.031>
- Ravey, A. (2012) *Design and Control Strategy of Powertrain in Hybrid Electric Vehicles*, Dissertation, University of Technology of Belfort-Montbéliard, <https://theses.hal.science/tel-00863541>
- Rosario, L.C. (2007) *Power and Energy Management of Multiple Energy Storage Systems in Electric Vehicles*, <http://hdl.handle.net/1826/2992>
- Sabri, M.F.M., Danapalasingam, K.A. and Rahmat, M.F. (2016) 'A review on hybrid electric vehicles architecture and energy management strategies', *Renewable and Sustainable Energy Reviews*, Vol. 53, pp.1433–1442, <https://doi.org/10.1016/j.rser.2015.09.036>
- Shuai, Z., Li, C., Gai, J., Han, Z., Zeng, G. and Zhou, G. (2019) 'Coordinated motion and powertrain control of a series-parallel hybrid 8×8 vehicle with electric wheels', *Mechanical Systems and Signal Processing*, Vol. 120, pp.560–583, <https://doi.org/10.1016/j.ymssp.2018.10.033>
- Silvas, E., Hofman, T., Murgovski, N., Etman, L.P. and Steinbuch, M. (2016) 'Review of optimization strategies for system-level design in hybrid electric vehicles', *IEEE Transactions on Vehicular Technology*, Vol. 66, No. 1, pp.57–70, doi: 10.1109/TVT.2016.2547897.
- Song, J. (2018) 'Integrated vehicle dynamic controls using active rear wheel steering and four wheel braking', *International Journal of Vehicle Systems Modelling and Testing*, Vol. 13, No. 1, pp.26–43, <https://doi.org/10.1504/IJVSMT.2018.094585>
- Tran, D.D., Vafaiepour, M., El Baghdadi, M., Barrero, R., Van Mierlo, J. and Hegazy, O. (2020) 'Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: topologies and integrated energy management strategies', *Renewable and Sustainable Energy Reviews*, Vol. 119, 109596, <https://doi.org/10.1016/j.rser.2019.109596>
- Wainer, G. (2002) 'CD++: a toolkit to develop DEVS models', *Softw Pr. Exper*, Vol. 32, pp.1261–1306, <https://doi.org/10.1002/spe.482>
- Wang, X.M., He, H.W., Sun, F.C. and Zhang, J.L. (2015) 'Application study on the dynamic programming algorithm for energy management of plug-in hybrid electric vehicles', *Energies*, Vol. 8, No. 4, pp.3225–44, <https://doi.org/10.3390/en8043225>
- Wu, Y., Tan, H., Peng, J., Zhang, H. and He, H. (2017) 'Deep reinforcement learning of energy management with continuous control strategy and traffic information for a series-parallel plug-in hybrid electric bus', *Applied Energy*, Vol. 247, pp.454–466, <https://doi.org/10.1016/j.apenergy.2019.04.021> Get rights, and content
- Xiong, S., Zhang, Y., Wu, C., Chen, Z., Peng, J. and Zhang, M. (2021) 'Energy management strategy of intelligent plug-in split hybrid electric vehicle based on deep reinforcement learning with optimized path planning algorithm', *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, Vol. 235, No. 14, pp.3287–3298, <https://doi.org/10.1177/09544070211036810>
- Xun, Q., Liu, Y. and Holmberg, E. (2018) 'A comparative study of fuel cell electric vehicles hybridization with battery or supercapacitor', *Proceedings of the 2018 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (SPEEDAM)*, June, IEEE, Amalfi, Italy, doi: 10.1109/SPEEDAM.2018.8445386.
- Zacharewicz, G. (2006) *Un environnement G-DEVS/HLA: application à la modelisation et simulation distribuee de workflow*, In Sciences de l'ingénieur (physics), Université de droit, d'économie et des sciences – Aix-Marseille III, France, Français. tel-00173633., <https://theses.hal.science/tel-00173633>
- Zeigler, B.P. and Sarjoughian, H. (2003) *Introduction to DEVS Modeling and Simulation with Java: Developing Component-Based Simulation Models*, Technical Document, University of Arizona, <http://itsys.hansung.ac.kr/devs/CBMSManuscript>

- Zeigler, B.P., Praehofer, H. and Kim, T.G. (2000) *Theory of Modelling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems*, 2nd ed., Academic Press, San Diego, <https://doi.org/10.1002/rnc.610>
- Zhang, X. and Mi, C. (2011) *Power Systems: Vehicle Power Management: Modeling, Control and Optimization*, Springer, London, doi: 10.1007/978-0-85729-736-5.

Note

¹Linguistic variables are used in fuzzy systems to express fuzzy values mathematically. The values of linguistic variables can be given using Membership Functions (MF) which can range from 0 to 1 with constant values.