IEEE Open Journal of
Vehicular Technology

Received 1 July 2020; accepted 4 August 2020. Date of publication 20 August 2020;
date of current version 1 September 2020. The review of this article was arranged by Associate Editor C. C. Mi.

Digital Object Identifier 10.1109/OJVT.2020.3018146

Intelligent Energy Management Systems for Electrified Vehicles: Current Status, Challenges, and Emerging Trends

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This work was supported in part by, thanks to funding from the Natural Sciences and Engineering Research Council of Canada (NSERC), NSERC Industrial Research Chair in Electrified Powertrains, and in part by Canada Research Chair in Transportation Electrification and Smart Mobility.

ABSTRACT Powertrain electrification has heightened the need for an energy management strategy, which has been a continuing concern in the development of electrified vehicles. The energy management control unit manages power flow between different energy sources in an electrified powertrain that directly affects vehicle performance. Developing an energy management strategy that is compatible with different real-world driving scenarios has opened a significant field of study for researchers. Recent advances and progress in intelligent control approaches have facilitated developing an intelligent energy management strategy. However, there are inadequate numbers of studies on the latest energy management strategies. The presented review paper aims to provide the requirements of intelligent energy management strategies as well as a new categorization of them into principle-based, data-driven, and composite methods. Besides, enabling technologies for implementing an energy management system with a comparison of different controller chips are described to give readers an experimental view. Future trends and existing challenges are presented, which generate fresh insight into energy management strategies.

INDEX TERMS Data-driven methods, electric vehicles, intelligent energy management strategy, reinforcement learning, powertrain architecture.

I. INTRODUCTION

Lives on earth have been drastically affected by the air pollution generated from vehicle emission, and global warming has caused drastic climate changes. One of the promising solutions is shifting toward fuel-efficient vehicle and electrification transportation. Combining different sources of energy such as a battery, an ultracapacitor (UC), a fuel cell (FC), and an internal combustion engine (ICE) can help decrease fuel consumption and emissions.

Pure electric vehicle (PEV), which has zero emission, seems like a feasible solution, but its shorter operating range compared to a conventional vehicle and the insufficient infrastructure to accept this technology have limited its accessibility. The limited charging station, long charging time, immature battery technology, high cost, and issues that happen to the power network should be addressed for going toward electrifying transportation [1]. Therefore, hybrid electric vehicle (HEV) which consists of an ICE with at least one electric machine (EM) is more popular. The added degree of freedom from the EM in HEVs brings more complexity in powertrain, however, this results in better performance, high power, and low acoustic noise in comparison to conventional vehicles.

Energy management strategy (EMS) tries to navigate energy between several energy sources considering one or multiple objectives while satisfying the driver's power demand. Energy consumption minimization, improving drivability, safety, increasing component lifetime, and emission reduction can be considered as an objective for an EMS problem. Drivability refers to the driver's comfort in terms of smooth gear shifting, low driveline vibrations and, reasonable engine on/off switches [2]. Safety focuses on tolerating possible faults that can occur in the vehicle components [3]. Carbon monoxide

(CO), hydrocarbons (HC), and nitrogen oxide (NO) are regarded as tailpipe emissions [4].

There are many publications for EMSs with applications mostly in HEVs. These methods are generally categorized into rule-based and optimization-based methods. In rule-based methods, rules are achieved through engineers' knowledge, in addition to trial and error. Since the rules are driven without any prior knowledge of drive cycles, rule-based methods failed to address the optimal EMS [5]. In contrast, optimization-based methods derive optimal control inputs for powertrain components with the goal of mostly improving fuel economy. Optimization-based methods are generally classified into global optimization-based and real-time methods [6]. The global optimization-based method considers the energy management problem for a complete and single driving cycle. Regarding their high computational time, they cannot be implemented in real-time directly. Real-time methods implement instantaneous optimization problems that only consider the current state of the system. Even though real-time EMSs yield online capable approaches, they are sensitive to different driving cycles.

Developing an approach with a tradeoff between simplicity of rule-based methods, optimality of global optimization approaches, and real-time capability of real-time EMSs has been a concern for researchers. A vehicle compatible EMS with the ability to adapt to its environment and low computational resources would be considered as an intelligent energy management strategy (iEMS). Optimization-based approaches can be modified by combining with state of the art algorithms to satisfy iEMS requirements. With emerging data mining techniques and machine learning tools, EMSs are being driven towards data-based methods with the capability of adapting to real world driving situations. Computational burden, experimental implementation, and optimal performance are the remaining challenges that should be investigated. The detailed requirements, classification, and challenges of iEMSs are further addressed in this paper.

There is a large volume of published reviews which study EMSs [7]–[11]. Authors in [3] have attempted to focus on EMSs which are implemented in HEVs based on bibliometrics, by considering both qualitative and quantitative analyses. Authors in [12] have categorized EMSs into online and offline strategies, along with describing different vehicle modeling techniques. Authors in [13] have formed a new classification of EMSs in terms of a hardware implementation for HEVs. The existing reviews have been mostly restricted to conventional EMSs and have not dealt with the control architecture with in-depth description of real-time optimization. The current study will address new trends in EMSs and suggest a novel categorization for iEMSs in electrified vehicles.

The remainder of the paper is organized as follows: Section II discusses different powertrain architecture followed by a brief introduction of energy sources. Electrical and electronic (E/E) architectures of electrified vehicles are explained in Section II. Section III categories iEMSs into three main categories. Each category is established, and the main challenges are addressed. Future trends and developing approaches are given in Section IV. Existing technology for implementing iEMSs is presented in Section V. Finally, Conclusions are summarized in Section VI.

II. CURRENT ELECTRIFIED VEHICLE ARCHITECTURE

The architecture that the EMS needs to control must be defined. Without a specified architecture, the EMS cannot be optimized or realized. In this section, electrified powertrain architectures, including its energy sources, propulsion devices and interfacing components are discussed. The two most popular E/E architectures are presented to provide the readers with a proper background on why, where, and how the EMSs are introduced for the appropriate vehicle architectures. The future of mobility not only depends on the electrified, automated and connected vehicles but also the devices in the vehicles [14].

A. ELECTRIFIED POWERTRAIN ARCHITECTURES

The electrification of the powertrain domain has garnered a lot of interest in the last couple of years due to the advancements made in electrical technology for energy sources, power conversion components, and different types of loads. Until recently, ICE has been the main propulsion component of the powertrain in conventional vehicles, which is supplied directly by petroleum sources [15]. Other means of energy sources have been introduced and researched, to ensure the automotive industry does not impact the environment negatively. As a way of introducing electrical energy sources, HEVs have been introduced in such a way that another energy source is used in conjunction with the ICE. The HEV has been a practical way of introducing sustainable and renewable energy sources into vehicles without disturbing the current infrastructure and causing too many risks in terms of safety and environmental impact.

Following the HEV, there are two other main electrified vehicle powertrain architectures that were studied, which are mentioned below and are illustrated in Fig. 1 [16]–[18]:

- Pure Electric Vehicle
- Hybrid Electric Vehicle
- Fuel Cell Hybrid Electric Vehicle

Each one of the above mentioned powertrain architectures is designated with different, but similar types of energy devices. Each architecture integrates the energy sources differently, but with similar technologies. Battery, supercapacitor (SC), UC, and thermal or mechanical energy sources can be used as energy sources in the architectures.

Batteries have been widely used in all types of vehicle architectures, including the conventional ICE vehicle for the low voltage electronics [20]. Battery maturity has reached a certain level where its use in both household and commercial industries has been widely accepted [21]. Batteries also offer the ability to be recharged during regenerative braking periods of the vehicle, which can be very advantageous, since batteries' energy density is smaller compared to nonrenewable fuels. Three of the main types of battery cell technologies

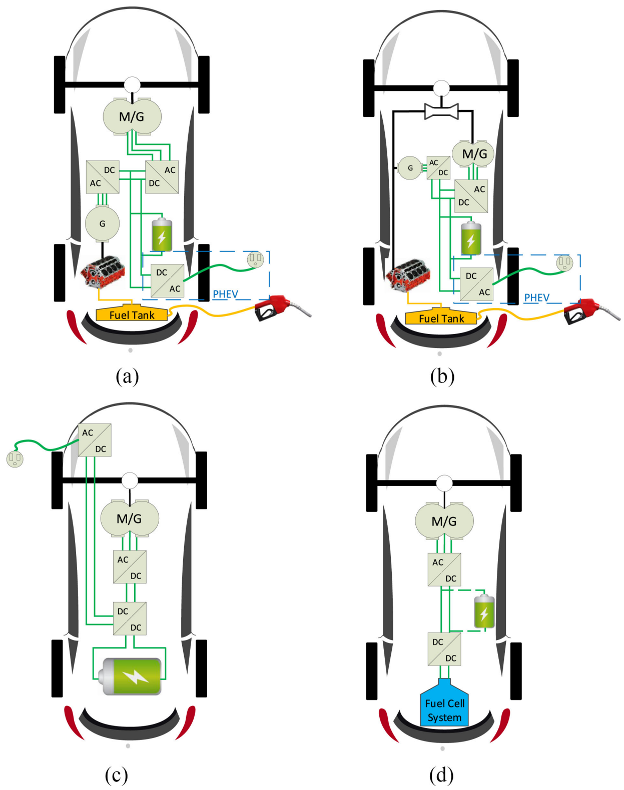


FIGURE 1. Main electrified powertrain architectures [16], [17], [19]. (a) Series Plug-in hybrid electric vehicle (b) Parallel Plug-in Hybrid vehicle (c) Pure electric vehicle (d) Fuel cell electric vehicle.

widely used today in xEVs have been the Lead-acid, Nickel-based, and Lithium-ion based batteries. Lead-acid batteries are common in household and commercial applications since they tend to be one of the cheaper solutions in battery cell technologies [22]. They also tend to have good enough efficiency and fast response to be incorporated in electrified vehicles. However, there are certain drawbacks associated with lead-acid batteries such as their negative impact on the environment, low specific energy, and their need to be replaced quite frequently. Nickel-based batteries have been used in HEVs for 14 years and manufactured mostly by Panasonic and Primearth EV Energy (PEVE) [22]. The power and energy density of the nickel-based battery, are significantly different from its counterpart of lead-acid. However, nickel-based suffer from a high self-discharge rate that would not benefit PEV with such technology since its range would be significantly affected. According to the detailed analysis of different battery chemistry in [20], lithium-ion batteries have unprecedented performance over the other technologies due to their higher energy density, no memory effect which increases its lifetime, and less environmental impact.

SCs and UCs employ both electrostatic and electrochemical storage to be able to deliver electric power. Different than traditional capacitors, UCs have been used to enhance traditional energy storage systems (ESS) in terms of lifetime and power delivery [23]. UCs have been traditionally used whenever immediate spikes of power are demanded by the load since they have a high power density [24], [25]. This method has been used to increase the lifetime of lithium-ion battery or just to ensure the power demand is met within a small time frame. Another positive aspect of UC is its long lifetime, which is noticeable in comparison to batteries.

FC energy sources have been widely used in fuel cell hybrid electric vehicle (FCHEV) in both civilian vehicles as well as in-city transit buses [26]. FCs are electrochemical energy sources that produce electrical energy through a chemical reaction between the oxidant at the cathode and the fuel atoms at the anode of the device [26]. FCs, in contrast to batteries, need an unceasing source of fuel in addition to oxygen to operate [20]. The different types of FCs are categorized based on the electrolyte substance. Proton exchange membrane fuel cells (PEMFCs) are dominant in transportation due to high efficiency, high power density, and low-temperature operation. However, low performance at high current density, high cost, and durability are remaining problems of using PEMFCs in vehicles [27].

Other sources of ESS consists of thermal and mechanical devices. In mechanical ESS, the flywheel can be used in conjunction with ICE, or other rotating components since the flywheel is able to store kinetic energy, and the accumulated energy is proportional to its rotational velocity [28]. The flywheel tends to be an attractive solution whenever the vehicle exhibits high or medium power demands [29]. They are favorable in terms of their lifetime (>20 years) as they have a large number of charge/discharge cycles, which is independent of temperature [30]. A disadvantage of the flywheel is that it tends to be quite heavy and bulky since the energy storage capability is proportional to the speed but as well as the inertia of the flywheel which is determined by its mass and geometry. A type of thermal ESS is the thermoelectric generators (TEGs). Using the Seebeck effect, TEGs are solid-state devices that help to regenerate the energy lost through heat within vehicle components such as ICE, exhaust systems, power converters, and other heat-generating components [31].

All of the aforementioned energy sources are used differently within different architectures of an electrified vehicle. The architecture of the vehicle highly dictates how the conversion and transfer of power are performed. Based on the three main architectures mentioned above, the most popular option of architectures for the electrified vehicle has been the HEV [16]. Many different HEV architectures imply many different possibilities to integrate the ICE with an electric battery or other energy sources. Some of the different HEV are listed below:

- Series Hybrid Electric Vehicle (SHEV)
- Parallel Hybrid Electric Vehicle (Parallel HEV)
- Series/Parallel Hybrid Electric Vehicle (SPHEV)
- Plug-In Hybrid Electric Vehicle (PHEV)

In Series Hybrid Electric Vehicle (SHEV), only the electric motor drives the wheels, and ICE has no direct mechanical connection with the wheels. This permits the ICE to perform at its maximum efficiency which is very useful for heavy commercial vehicles, military vehicles and as well in buses [12], [32]. A SHEV with plug-in capability is shown in Fig. 1(a). For parallel HEV architectures, the use of electric motors and ICE is in parallel to drive the wheels. The parallel HEV architecture (with a plug-in) can be seen in Fig. 1(b). Toyota, Ford and Lexus have been using this configuration for quite a while [12]. SPHEV architectures have been used in small automobiles and provide paths for ICE to wheels as well as electric motors to wheels by using planetary gearsets [12], [33]. Lastly, for all of these architectures, a plug-in capability can be introduced which lets the owner of the vehicle charge the vehicle whenever not in use. This ensures that there is a maximum amount of electrical energy stored whenever the vehicle would pursue a journey. This can maximize range and can be helpful in reducing fuel consumption.

One of the simplest solutions but also very attractive one to vehicle electrification is the PEV which is shown in Fig. 1(c) [34]. The PEV has zero emissions due to its energy being solely powered by an electrical energy source. The architecture is simple due to its direct energy transfer of DC voltage to AC voltage and vice versa through three-phase inverters and rectifier units [35]. The disadvantage with the PEV is that the most common and produced energy dense technology is the lithium-ion battery [22]. Due to the battery technology not being mature enough, energy densities like that of petrol cannot be attained yet with pure batteries [36]. Hybrid energy storage system (HESS) has been utilized in PEV to find a solution to the energy density problem. Solar panels have also been introduced to help extend the range in [37], [38] but has not been a preferred solution in civilian vehicles.

The last most popular architecture of an electrified vehicle is the FCHEV. It may not comprise of many components as shown in Fig. 1(d), but to integrate them together in a safe moving vehicle is the challenge [39]. FCHEVs have number of advantages than conventional ICE vehicles such as high conversion efficiency with flexible fuels with a high energy density, a relatively quiet operation compared to ICE, no emissions, waste heat recovery and durability [20]. Long driving range and short refueling time are the positive aspects of FCHEVs in comparison to their purely electric counterpart. Although having significant advantages over ICE vehicles, FCHEVs require having a large tank, thus requiring a large volume. Furthermore, FCHEVs exhibit low efficiencies whenever working with high power demand and also, their costs have been limiting their applications in civilian vehicles. Safety is paramount to the application of FCHEV and verification effort must be used to ensure the safety of the fuel.

B. ELECTRICAL AND ELECTRONIC ARCHITECTURES

The E/E architecture of such electrified vehicles described in Section II-A has come to a paradigm shift where the in-vehicle E/E architecture electronic control units (ECUs) that were connected in a central "Gateway" or "Plug-in" type of control architecture is moving towards a more distributed or centralized control architecture [40]. ECUs consist of embedded controllers that perform multiple functions in the vehicle to minimize the driver's effort of driving the car, ensuring safe control and monitoring of the vehicle components while also ensuring the entertainment systems in the vehicle are functioning properly. Most of the ECUs in conventional vehicles are mainly tasked to do a single vehicle function including but not limited to:

- Adaptive Cruise Control (ACC)
- Anti-Lock Braking System (ABS)
- Battery Management System (BMS)
- Engine Control Module (ECM)
- Light Switch Module (LSM)
- Park Distance Control (PDC)

In the conventional E/E architecture of a vehicle, there can be 70 to 100 ECUs with their own functions. The communication is performed on a dedicated "gateway" bus depending on the safety level of the ECU. The trend of electrification is pushing for a redesign of the E/E architecture of an electrified vehicle. This redesign step is coming from the bottlenecks found in the migration of xEV technologies where requirements such as flexibility, scalability, external communication, computing power, communication bandwidth and functional complexity are all increasing [41]. This increase has pushed the limits of current technology used in conventional vehicles and different types of communication architecture are needed along with different types of ECU distribution. Furthermore, having so many ECUs in the vehicle requires high qualification costs that can have a huge impact on the manufacturer of the vehicle [42]. Requiring many ECUs increases energy consumption which is non-ideal for xEVs where range is crucial and limited.

The move to centralized E/E architecture is inevitable but this has to come gradually as not to disturb the vehicle infrastructure. Some requirements for new E/E architectures consist of acquiring large amounts of environmental data along with many parallel computations to ensure proper processing of the vast amount of data [43]. The move from a distributed E/E architecture to a more centralized one has been adopted by two similar but different types:

- Domain Controller Architecture (DCA): Domain specific ECUs with possible domain overlaps through dedicated gateway.
- Zonal Controller Architecture (ZCA): Domain independent with a central in-vehicle/external computer with possible zone ECUs.

The DCA, a more centralized type of control architecture is taken at the vehicle level. Fig. 2 shows how such a domain controller architecture can look like based on a combination of [44]–[46]. Functions of traditional ECUs are merged together to make one powerful domain controller communicating through a dedicated inter-domain bus. To ensure proper domain configuration and functional safety of the vehicle, the domains must be grouped by subsystems that are classified in terms of physics and non-physics but also must have a high amount of synergy [14]. The main criterion is functional safety in terms of function combination in domains. If a failure

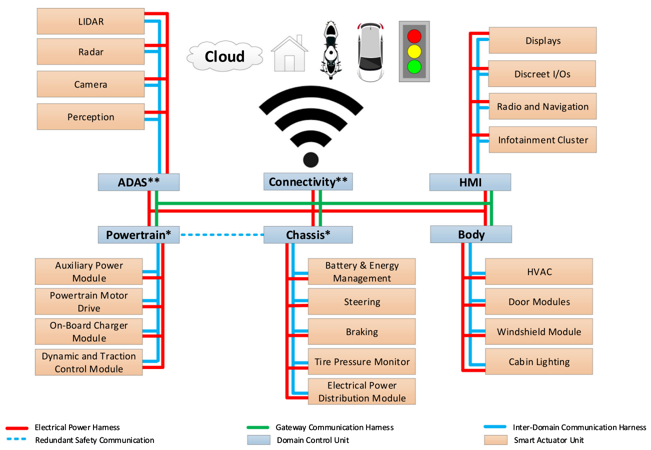


FIGURE 2. Domain controller E/E architecture example.

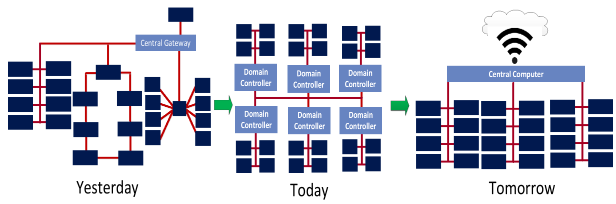


FIGURE 3. Migration of E/E architecture adoptions for new centralized cloud computing.

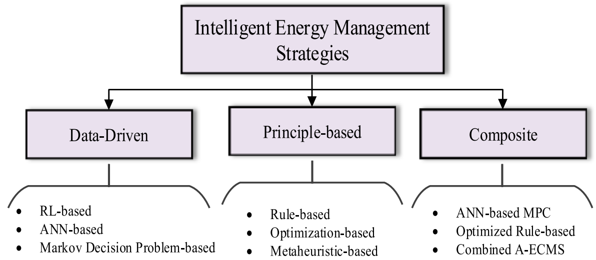


FIGURE 4. A classification of iEMSs into three categories: 1) Data- driven 2) Principle-based and 3) Composite methods.

occurs in one of the domains, the failure must be dealt with appropriately and not affect other domains while bringing the vehicle at a fail-safe state. The DCA can be separated into three different types of components where there are inter-domains, or better known as smart sensor/actuators, power domain controllers that combine multiple ECU functions together to ensure functional safety and performance and finally a central gateway to interconnect the domains. Some examples of the domains of a DCA based on Fig. 2 are listed below:

- Human Machine Interface (HMI)
- Autonomous Driving Assisted Systems (ADAS)
- Connectivity
- Body
- Powertrain
- Chassis

Each domain communicates through a central gateway to ensure data is transferred properly between inter-domains and domain controllers. Each inter-domain is comprised of smart actuators or smart sensors that communicate necessary data. An inter-domain could comprise electric motors, pumps, on-board chargers, x-by-wire for example. By using a DCA, each domain controller could use the same hardware, operating system, and software with just different software application layers. This would be extremely beneficial in terms of the costs of the manufacturers. The DCA has been a preferred choice for manufacturer's in today's volume production and premium vehicles but not in low price vehicles [14], [44].

As in the DCA, the ZCA must have the same requirements in terms of fail-safe, secure, upgradeable (software and hardware), connected, and self-aware/learning [47]. In the ZCA, a more centralized approach is being taken with the same goal of the DCA to minimize the ECU count in vehicles. Sensors and actuators communicate individually through their own dedicated communication bus to a very powerful centralized supervisory controller taking the decisions for each actuator/sensor function [48]. Furthermore, this architecture enables connectivity to external servers along with cloud computing and control of vehicles. This large step is complicated right now but a gradual step to that mindset is through the adoption of the ZCA by incorporating the DCA. Gradual migration of ECU functionalities must be performed to adapt to the infrastructure [49]. This gradual migration is shown in Fig. 3.

III. NOVEL CATEGORIZATION OF INTELLIGENT EMSS

Bestowed with the ongoing researches since the last couple of decades, competencies of EMS for an electrified powertrain have grown significantly. They seek to obtain methods with low computational load and compatible with a real-world situation along with optimal performance. There are relatively few studies describing the requirements of an iEMS and providing a categorization. Authors in [50] have highlighted real-time EMSs with an emphasis on the optimality of the control strategy. In this study, different approaches that can be integrated into EMSs are examined to enable energy management systems for real-time implementation. Authors in [51] have categorized the existing EMSs by considering data-based approaches such as machine learning-based EMSs. Overall, these aforementioned review articles indicate the need for a separate study that will enumerate the requirements of an iEMS. This review article intends to provide a comprehensive categorization of the existing iEMSs followed by a brief list of criteria, which should be satisfied by an EMS before being called an iEMS. It's noteworthy to mention that it is not intended here to furnish a comparison between ordinary EMSs and iEMSs but to rearrange the existing EMSs as per the following criteria.

A. REQUIREMENTS OF INTELLIGENT EMSS

A number of criteria are considered when an EMS features an intelligent controller. Several classical EMSs are excluded from being intelligent by introducing these eligibility criteria. For instance, dynamic programming (DP), which is a well-known global optimal approach, can not be called an iEMS since it does not satisfy the real-time capability requirement. Based on the authors knowledge and experience, the requirements for an iEMS are listed below:

1) The iEMS controller should be real-time implementable.
2) The iEMS controller can learn from its past external environment scenarios during real-world deployment.
3) The iEMS controller has the ability to analyze quantitative and qualitative data.
4) The iEMS controller is adaptive to new environmental scenarios or conditions for what the EMS controller has not been modeled within the simulation stage.
5) The iEMS controller adapted solution needs to converge. Ideally, this is for any EMS controller. No controller will be deployed if it is not converged to the assumptions of the designer.
6) The iEMS controller should be able to predict the future. This requirement is considered a possible soft requirement. As an example, model predictive control (MPC) approach has the ability to predict the future over the prediction horizon.

B. PRINCIPLE-BASED INTELLIGENT EMSS

There are two categories for the principle-based iEMSs which are rule-based and optimization-based algorithms. Rule-based approaches are frequently used in commercial vehicles such as the Toyota Prius and the Honda Insight [8]. Optimization-based methods include global and instantaneous optimization algorithms, that are employed for an EMS with the goal of improving fuel economy in most cases.

1) RULE-BASED

Rule-based methods are defined by a set of rules extracted from engineers' experience and knowledge. Besides, results are achieved by global optimization algorithms, that can be used to extract optimal rules for the specific driving cycle [52]. Rule-based methods offer several attractive features, which include simplicity, real-time capability, and easy implementation. Rule-based methods can be categorized into deterministic and fuzzy-based. Thermostat strategy [27], power follower [53], modified power follower [54], and state machine [55] are methods used for deterministic rule-based. Low efficiency regarding the high number of on and off power sources, and ignoring drivers power demand in defining rules are the main weaknesses of thermostat strategy [27]. Power follower provides a solution for drawbacks of thermostat strategy by considering engine as the main power source in the vehicle along with the battery state of charge (SOC) and driver's power demand as constraints [53]. The power follower method fails to consider fuel emissions and consumption; therefore, a modified power follower is proposed in [56].

Charge depleting-charge sustaining (CDCS) and blended strategy are two main deterministic rule-based methods that are used for a plug-in-hybrid electric vehicle (PHEV). In contrast to HEVs, PHEVs benefit from high capacity batteries. Therefore, the battery is in the charge depleting (CD) mode during most of the trip time. Rule-based methods that are defined for HEVs can be used for charge sustaining (CS) mode to avoid the battery depletion. In the CDCS strategy, the vehicle goes in electric mode until the battery reaches the specified SOC value (CD mode), and then the control strategy tries to keep SOC at this level (CS mode) until the end of the trip [57]. In a blended approach, the control strategy seeks to reduce the battery discharge rate by assisting the engine in CD mode.

Fuzzy rule-based is suitable for EMS of HEVs regarding the inherent feature of fuzzy logic, which allows a degree of uncertainty to inputs. One of the main positive aspects of fuzzy rule-based approaches is their robustness to input variations. Fuzzy based methods are divided into three main categories; conventional, adaptive, and predictive fuzzy EMSs [58]. Adaptive fuzzy tries to consider driving environment factors and make the method more robust to the environment. Predictive fuzzy, by employing driving history, can predict the future state and then decide to split the power. Reference [59] implements a predictive fuzzy-based method that benefits from a global positioning system (GPS) to inform of future traffic flow.

Despite the advantages that rule-based methods offer for an EMS, it does not directly consider fuel consumption or emission, as well as, it is not robust to imprecise measurements and component variations. Besides, they are based on engineers' expertise, and there is not any specific methodology for extracting rules. On the other hand, fuzzy rule-based methods fail to guarantee the optimal power split in an EMS. Also, definition for a set of fuzzy rules can be time-consuming and might not be ideal for real-world driving cycles.

2) OPTIMIZATION-BASED

Most of the review papers divide optimization-based methods to global optimization and real-time approaches. Global optimization methods can not be considered as iEMSs. Since global methods require the entire driving cycle information to minimize the cost function, they cannot be implemented in real-time. DP is a numerical backward global-optimization method based on Bellman's principle of optimality [60]. DP is computationally intensive and depends on the complete knowledge of the driving cycle. To evaluate iEMSs, DP results are mostly considered as a benchmark.

Real-time methods convert the global optimization problem to an instantaneous optimization. These methods minimize the cost function in the current state of vehicle performance instead of considering the entire trip. Equivalent consumption minimization strategy (ECMS) and MPC are the most popular methods which belong to this category. A brief introduction for each method is provided below:

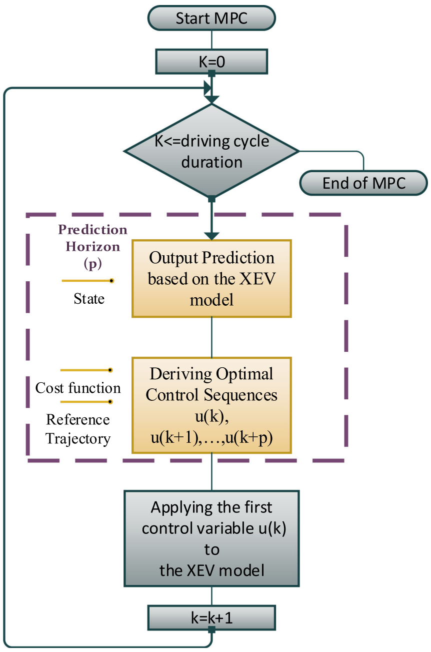


FIGURE 5. **The MPC control algorithm.**

ECMS: ECMS is established to facilitate the real-time implementation of EMSs [61]. This method considers the objective function as a summation of engine fuel consumption and battery equivalent fuel consumption. The additional term extends the ability of ECMS to consider the energy consumption of a powertrain rather than only fuel consumption of an ICE. Equivalence factor (EF) is the key issue in the performance of ECMS, which scales electric energy to fuel consumption. EF optimal value depends on the driving cycle. According to [62], inappropriate EF selection can lead to battery depletion or overcharging. Several methods are established to tune the EF real-time during vehicle operation. Adaptive ECMS (A-ECMS) has been developed to mitigate the EF dependency on driving cycle information. Authors in [62] have classified the A-ECMS to three methods that utilize different tools to adjust an EF value online. The tools are:

- Future driving cycle information predictor [63], [64]
- Pattern recognition algorithm [65]
- Battery SOC feedback [66]

In fact, the last method which is battery SOC feedback can be integrated into other A-ECMSs [66]. Even though ECMS is a sensitive approach to driving cycle information, a significant benefit of this approach is real-time implementation. Adaptive methods can be further investigated to provide an approach with results close to global optimal solutions by DP.

MPC: MPC strategy has several attractive features which make MPC effective for nonlinear, and multiple-input and multiple-outputs (MIMO) systems with constraints such as electrified vehicle powertrain [67]. Fig. 5 shows MPC algorithm steps. In contrast to DP where the optimization conducts over the whole driving cycle, in MPC, an optimization algorithm is implemented in a short time horizon in each time step that enables MPC for real-time implementation. The optimization part is employed to minimize the error between the predicted and the desired plant output along with fuel minimization or battery SOC sustaining goals. DP [68], quadratic programming (QP) [69], particle swarm optimization (PSO) [70], and other optimization algorithms can be employed for a short time optimization step. Once the control variables are calculated, the first control input applies to the electrified powertrain, and the prediction horizon shifts to the next time step. This process is repeated until the end of the trip. MPC requires high accuracy prediction information, which makes it computationally expensive for real-world implementation. Artificial intelligence and markov chain (MC) predictors are widely implemented for the MPC prediction part that are explained in detail in Section III-C2 and III-D1.

3) METAHEURISTIC-BASED

In mathematics, especially in optimization, metaheuristics are a category of decision making procedures, which can reach to close neighborhood of the global optimal solution (GOS) with far less computation efforts and with a limited amount of indispensable information. Metaheuristics may not yield exact GOS, but the proximity of the solution yielded by meta-heuristics to GOS is praiseworthy, especially with limited computational effort and information. That is why metaheuristics have attracted major attention from application-oriented research community and industry because they can afford to compromise little deviation from GOS at the expense of convenience in real-time implementation. Metaheuristics reach the near-GOS with a perfect balance between exploration and exploitation [71], [72]. Metaheuristics reduce the computational effort of searching near-GOS by avoiding a significant portion of the futile control space. Authors in [71] have made a notable contribution by presenting a comprehensive review of the application of different metaheuristics in solving multitudinous problems associated with PHEV. Such problems include the articulation of EMS, optimum component sizing, smart charging strategies, etc.

There are a lot of metaheuristics available such as PSO, a few varieties of PSO, genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), etc. PSO is a stochastic online optimization technique that employs different particles to randomly search for the suboptimal or optimal solution within the whole solution space [73], [74]. PSO reduces the computational time by not sweeping through all possible solutions, but randomly culminating in the suboptimal or optimal solution [75]. Quite a handful of literature implemented PSO offline for finding the optimal threshold parameters of a rule-based control which can be implemented in real-time [76]–[78]. Authors in [76] have optimized threshold parameters of a simple CDCS control strategy with PSO. Whereas, authors in [78] have articulated a rule-based EMS strategy whose threshold parameters are updated periodically with the help of PSO. The periodic parameters update process is triggered by a fuzzy drive cycle recognition system to make the rule-based control apposite for different types of drive cycles. Apparently, it seems that PSO might not be suitable for real-time implementation, but a few literatures [75], [79]–[81] made the online implementation feasible with reduced computational time. As far as the online performance is concerned, PSO can outperform not only the genetic algorithm, but other evolutionary algorithms [81]. Authors in [81] have presented an online and real-time PSO implementation for optimizing two control variables such as power-split ratio and gear number to assist a rule-based online control for the EMS. Although the PSO was not solely responsible for the EMS in this study, the implementation of PSO was at every time-step of online simulation. Authors in [80] have improvised the search method of the PSO to accelerate the search process and consequently managed to obtain better performance with less computational effort. Compared to traditional PSO, improved PSO (IPSO) accounts for the position of the worst particle while updating the velocities of every particle at each iteration. Authors in [81] implemented dynamic PSO (DPSO) and proved its superiority over traditional PSO. Real-time hardware-in-the-loop (HIL) simulation results of an optimal torque distribution strategy for an EV with three electric motors corroborate that instantaneous optimization through PSO can be achieved decent proximity with the global optimal result obtained by DP [79].

GA is generally not implemented online due to its computational burden and incumbency of prior knowledge of the drive cycle. However, GA can be appointed as a local optimizer using a sliding backward time window, and the local optimization can be executed in real-time [82]. Authors have proposed a GA-based online optimization for the EMS of an electric vehicle (EV) with a HESS.

Several researchers have marked SA as a remarkable metaheuristic to be appointed in the EMS for electrified powertrains in recent years. Although none of the applications were iEMS for HEVs, SA has been employed as a real-time implementable local optimizer, to optimally distribute the power between battery and UC for an EV [83], [84]. SA culminates to its best performance when the search space is restricted by certain rules [83], [84]. Similar behavior is also exhibited by PSO in real-time HIL simulation, when its search space is dynamically constricted by a set of rules [85]. In [84], SA has been appointed as a local optimizer, finding instantaneous optimal power-sharing between UC and the battery in real-time at an interval of 10 milliseconds. In a nutshell, metaheuristics carry great potential in the form of real-time implementation in elevating the iEMSs to a new level.

C. DATA-DRIVEN INTELLIGENT EMSS

The system dynamics of the powertrain are incumbent on both analytical and numerical methods. Data-driven approaches can be used to replace any kind of incumbency of system dynamics, such as the dynamics of a physical system, prediction system, and classification method. Whenever there is a difficulty in mathematical modeling of an implicit system dynamics, data-driven approaches assist as a savior to model

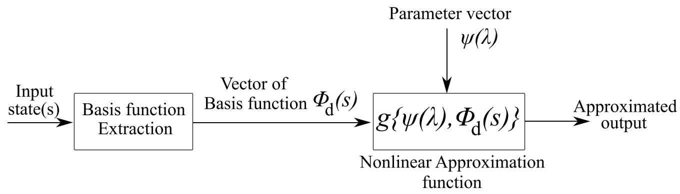


FIGURE 6. A simple concept of nonlinear function approximation.

it. Data-driven approaches primarily focus on mimicking the system dynamics through the mapping of input to output relationship.

1) ARTIFICIAL NEURAL NETWORK-BASED

Multi-layer perceptron, widely known as artificial neural network (ANN), is the most abundantly used nonlinear function approximator in various fields of data science. ANNs are appropriate for deciphering the dubious input-output system dynamics, which is highly nonlinear and difficult to model with an analytical approach.

Bestowed with effective learning algorithms, ANNs are highly competent in deciphering the inherent input-output characteristics of any physical system if sufficient data are available. Training methods can be broadly categorized into supervised learning and unsupervised learning.

The architecture of a generalized nonlinear approximator can be expressed with the following relation as given in [86]:

$$\tilde{Q}(s; \psi) = g(\psi(\lambda)\Phi_d(s)) \tag{1}$$

where $g(.)$ is a nonlinear function representing the architecture of the approximator, $\Phi_d(s)$ is the vector of feature or basis functions of the states, and ψ is the parameter vector as shown in Fig. 6.

For EMS application, ANN can represent the iEMS controller, velocity predictor [87], model of vehicle [88], and driving trends predictor. Quality of predictive EMSs highly depends on the accuracy of the predicted variables. Authors in [89] have implemented three ANNs for predicting road types, driving trends, battery power, and engine speed. The performance of iEMS with the implementation of ANNs is directly governed by the quality of the training data-set. For the ANN-based iEMSs, DP is generally chosen as the source of the training data since DP can yield exact global optimal results in comparison with other global optimization techniques such as stochastic dynamic programming (SDP), GA, PSO, and evolutionary algorithm (EA) [90].

Both performance and computation time of DP depend on the discretization of state and control variables along with the dimension of state and control space. The computational time shoots up exponentially as the discretization becomes finer.

Needless to say, that curse of dimensionality will be inevitable if either dimension or discretization of state or control variables increases beyond a certain limit, as depicted by Table 1. τ_{ice}, ω_{ice}, and gear mode are typical control variables.

TABLE 1. **Proof of "*curse of dimensionality*" as the Number of Discrete Variables Increases**

Case	State variables (discretization)				Control variables (discretization)			Required cells for Dynamic programming
2 states, 1 control	Speed (20)	Acceleration (20)			τ_{ice} (20)			$20 \times 20 \times 20 = 8000$
3 states, 2 controls	Speed (20)	Acceleration(20)	Road-grade(5)		τ_{ice} (20)	ω_{ice} (20)		$20 \times 20 \times 5 \times 20 \times 20 = 400000$
3 states, 2 controls	Speed (40)	Acceleration(20)	Road-grade(10)		τ_{ice} (40)	ω_{ice} (40)		$40 \times 20 \times 10 \times 40 \times 40 = 1.28 \times 10^7$
4 states, 3 controls	Speed (40)	Acceleration(40)	Road-grade(10)	Power-demnad (40)	τ_{ice} (40)	ω_{ice} (40)	Gear Mode(5)	$40 \times 40 \times 10 \times 40 \times 40 \times 40 \times 5 = 5.12 \times 10^8$

Consequently, gathering data for ANNs in an iEMS is a time-intensive process. In order to expedite the process of data collection, researchers are focusing on finding new strategies yielding near-optimal offline control with far less computational time [91].

2) MARKOV DECISION PROBLEM-BASED

It is important to take a look at the literature for finding different prediction methods adopted and what aspects of the driving scenario are predicted by those methods. Markov chain model (MCM) is a popular method to predict different aspects of future driving scenario. According to MCM, the probability of getting a certain state in the next time-step only depends on the state of the current time-step. This probability is numerically referred to as transition probability matrix (TPM) in probability terminology. Authors in [92] have presented an iEMS framework, which is comprised of an MCM predicting road grade, speed of vehicle, vehicle stop-start or acceleration-deceleration, and SDP acting as an optimization tool over prediction horizon, for a parallel HEV.

TPM is the major characteristic element of overall markov decision problem (MDP) and hence, governs the overall execution process of MDP. If enough historical data of the driving scenario available, a static TPM can be constructed and can be used for predicting N-step values of future driving scenarios in real-time applications [92], [93]. However, enough historical data is often not available and an updating TPM can be articulated in such a case [94]. The N-step MDP can be solved through SDP in offline to obtain optimal control over N-step future horizon if the static TPM is available. But, it is convenient to use reinforcement learning (RL) [95] or adaptive dynamic programming [94] to solve the MDP engendered from an updating TPM. QP has also become a lucrative option as an optimization strategy for the MDP, associated with online updating TPM since QP's feasibility in real-time implementation [96].

3) REINFORCEMENT LEARNING-BASED

RL is one of the machine learning methods that has gained a lot of attention nowadays and is applied in many different fields such as robotic control, traffic management, space exploration rovers, and autonomous vehicles. RL-based agents are especially tailored for sequential decision making, where the long-term return is more prioritized rather than short-term rewards. The agent and environment are the two cardinal parts of RL. The agent's capability of yielding better control decisions improves through reinforcement learning as the agent accumulates more experience [97].

In RL, the agent interacts with the environment which can be mathematically modeled through the states $(S_t) \in \mathcal{S}$, actions $(A_t) \in \mathcal{A}$, and reward function $(r_t) \in \mathcal{R}$. The sequential decision making along with the sequence of environment states is widely known as MDP. The noteworthy characteristic of MDP is the fact that the agent does not need to look through the history of the environment's states in order to make a decision at the present time-step. The underlying concept behind such a fact is the property of state variables that probability of landing upon S_{t+1} depends only on the S_t and not on any other states in the past. The dynamics of MDP is defined by the probability of moving to state S' at time $t+1$ if action (A_t) is applied on S_t at time t as given in [98]:

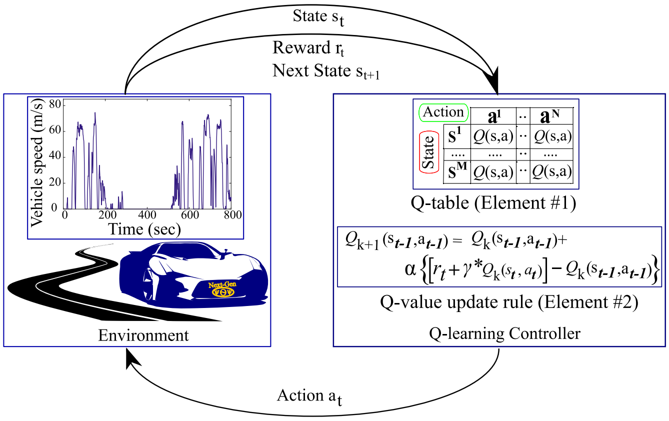
$$\mathcal{P}^{A_t}_{S_t S'} = Pr(S'|S_t, A_t) \tag{2}$$

This probability of transitioning from the current state to the next state can be stored for all time-steps in a matrix format, known as TPM. Technically, the RL agent should find an optimal policy function $(\pi(S))$ which dictates the rule of finding an optimal action at a given state. The RL agent wields two types of goodness functions, i.e., state value functions $(V(S_t))$, and action value functions $(Q(S_t, A_t))$ for finding the optimal policy function.

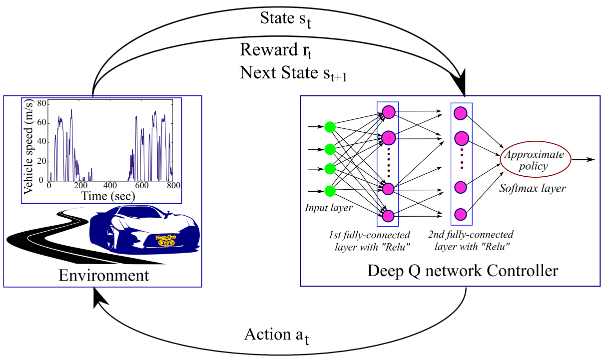
$\mathcal{P}^{A_t}_{S_t S'}$ is the cardinal characteristics governing the model of any given MDP. If the model of a given MDP is available to the RL agent for the entire MDP, DP-based algorithms, which are also known as model-based algorithms, can be employed to find the global optimal policy for the MDP. However, in real-world situations, where prior information of the entire MDP model is not available to the RL agent, model-free algorithms such as temporal difference (TD) learning algorithms are most appropriate for finding near-optimal policy [97].

Authors in [99] have implemented an iEMS based on RL algorithm and the TPM of states, which are driver power demand, vehicle speed, and battery SOC, is calculated offline by different driving cycles for the proposed strategy. On the other hand, authors in [100] have proposed an iEMS which updates the TPM of driver's power demand in real-time to find the optimal policy for the RL agent. As far as the real-time implementation is concerned, only a few papers have presented the real-time implementation of RL in their literature. However, there are a handful of papers that have described the prospect of real-time implementation. The proposed RL algorithm for a hybrid electric tracked vehicle (HETV) in [101] is implemented through HIL test and it is compared with DP to validate its optimality and adaptability.

Similar to DP, as mentioned in III-C1, implementation of RL-based algorithms can be impeded with the curse of dimensionality if they are implemented through the tabular method. Even if we use a coarse discretization, the number of states and of feasible actions can be as high as for instance 4000 and 2500, respectively [102].



(a) *Q-table based Reinforcement learning agent*



(b) *Deep neural network based Reinforcement learning agent*

FIGURE 7. **DRL architecture. Left box in both (a) and (b) shows the environment comprising vehicle and drive cycle. The right hand side box in (a) represents a Q-table based RL agent whereas, it is replaced with a deep-Q-network in DRL as shown in (b).**

A balance between exploration and exploitation is another important factor governing subtle characteristics of the RL algorithm. A higher value of the exploration-exploitation ratio is highly recommended at the beginning of the agent training to encourage exploration throughout the entire action space. Authors in [103] have given detailed analysis of selecting random exploration rate value between 1% to 20% and its impact on vehicle performance and fuel consumption for an HEV.

Lately, the application of deep reinforcement learning (DRL) for implementing EMSs has been soaring from last five years [104]. DRL employs deep neural network (DNN) in order to express state value function $V(S_t)$, action value function $Q(S_t, A_t)$, and policy function $\pi(S)$ with function approximation instead of tabular approach and hence, eradicates the hindrances posed by large number of quantized state and action variables. Authors in [105] have employed a DRL-based approach for Q-learning where the agent leverages both offline and online learning for better performance. Performance of the proposed iEMS is compared to that of rule-based EMS and it is shown that the iEMS leads to a reduction of fuel consumption by 10.09% under the urban dynamometer driving schedule (UDDS). Fig. 7 depicts an overview of DRL.

D. COMPOSITE INTELLIGENT EMSS

Composite iEMS is a growing topic which has been getting attention recently. Composite methods combine intelligent control methods and global optimization tools into principle-based methods to mitigate their imperfections.

1) ARTIFICIAL NEURAL-NETWORK BASED MPC

The predicted output in an MPC algorithm should follow the reference trajectory, and the MPC performance highly depends on the prediction accuracy. The prediction task can be done in different ways. Authors in [106] have classified MPC approaches based on the method of prediction to frozen-time, prescient, artificial intelligence, exponential varying, telematic, and stochastic MPC.

There are several publications on ANN- based predictor for MPC-based iEMS [107]–[109]. A radial basis function (RBF) ANN velocity predictor is employed in [108], which is trained with four different driving cycles to cover both highway and urban city driving conditions. The simulation results show that the predictive EMS consumes 659.1 g fuel over the same trip as DP consumes 628.5 g. An MPC based iEMSs is proposed to increase the battery life of an EV in [109]. ANN-based short term velocity predictor is applied in combination with the MPC algorithm that leads to a 17.8% improvement in battery life in comparison to the three different methods, which includes a rule-based, instantaneous approach, and an SC voltage based strategy.

2) OPTIMIZED RULE-BASED

Rule-based methods can be implemented in real-time and they are easy to understand. However, they do not offer optimal performances in EMSs. Rule-based EMS includes different operation mode, which is switched by threshold parameters of battery SOC, vehicle speed, and torque capability of energy sources. Section III-B3 provides some studies which implement PSO in combination with rule-based methods. In addition, there are more studies that have attempted to implement an optimization algorithm for optimizing threshold parameters [110]–[112]. Authors in [113] have employed GA optimization to optimize different threshold parameters such as the maximum and minimum value of SOC and electric launch speed of a rule-based EMS in a parallel HEV.

The integration of optimization methods is not limited to deterministic rule-based approaches. Authors in [114] have optimized the rule set and membership functions of a fuzzy logic method by the PSO algorithm to yield a better fuel economy. Authors in [114] have also compared the performance of the fuzzy optimized method with that of a deterministic rule-based approach. The optimized method with the PSO algorithm leads to 10.26% reduction in fuel consumption.

3) COMBINED A-ECMS

A-ECMS seeks to update EF to ensure better fuel economy and charge sustenance of the battery in real-world driving.

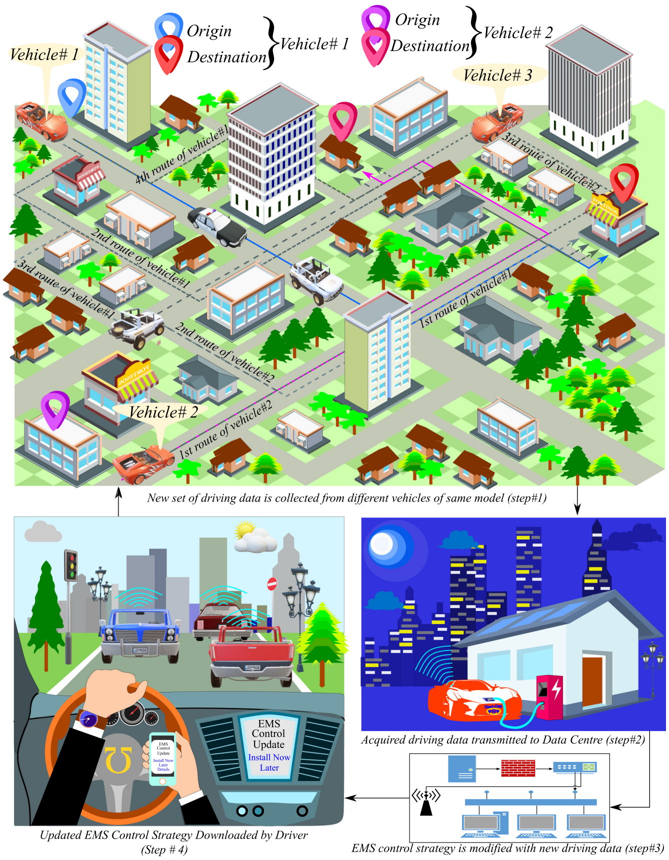


FIGURE 8. One of the promising concepts of the future trend on a periodic update of EMS control strategy. A set of vehicles with same electrified powertrain will acquire driving data for a predefined period (step#1), the acquired data will be uploaded to cloud-computing servers while the vehicle is externally recharged (step#2), new EMS control will be generated at the server based on the recent driving pattern of the vehicles (step#3). The availability of the most updated EMS control will be notified to each of those vehicles through both smartphone and vehicle infotainment system (step#4).

Authors in [64] have suggested implementing a velocity predictor to ensure the adaptation of EF. Authors in [63] have conducted an A-ECMS which updates EF periodically by means of an ANN short term velocity predictor. The results show 3% improvement in comparison to a traditional ECMS. A convolutional neural network (CNN) is employed in [115] to address velocity prediction by considering vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication technology. Three different scenarios are considered for city traffic modeling. A-ECMS block tunes the EF by accessing to predicted velocity and battery SOC feedback. Predicted A-ECMS proves 0.2% to 5% fuel economy improvement for three different scenarios. Driving pattern recognition algorithms such as fuzzy and machine learning methods can be used to improve an A-ECMS performance. Authors in [116] have used k nearest neighbor (KNN) to classify different driving styles. A driving simulator is used for gathering the driver's driving style in order to feed the KNN module. The results confirmed an 8.28% average improvement for different driving styles over traditional ECMS.

IV. FUTURE TRENDS OF INTELLIGENT EMSS

So far, studies on iEMSs of electrified powertrain vehicles have been carried out by many different methods. A considerable amount of work will need to be done to validate the reliability of these methods. A systematic blueprint of experimental validation should be developed for each of the iEMSs, reviewed here, to corroborate their reliability and feasibility in actual deployment. This review provides the following insights for future research in the field of iEMS:

1) Additional work is required to ameliorate the existing demerits of implemented RL algorithms. The agent should be able to take more dimensions of input state variables in order to discriminate multiple real-world driving scenarios with subtle differences. Q-table based agents become incompetent to handle more dimensions of the state variable.

Consequently, DNN-based agents are becoming an enticing option to researchers. Various dual ANN-based agent structures such as policy gradient (PG), deep deterministic policy gradient (DDPG), advanced asynchronous actor-critic (A3C) should be explored for faster convergence. Such advanced agent structures should be validated in online or real-time emulation along with their offline design and simulation. It would be an exciting and obviously challenging task to design and develop any of the RL agents, reviewed here, for a couple of real-world driving missions and, test its performance in another unfamiliar driving mission. There is ample room for further progress in DRL to make the results of iEMS controller adaptive and much closer to the global optimal solution.

2) Most of the work in the field of EMS is limited to the simulation level. It is needed to go beyond papers and implement the suggested methods experimentally to see the real-world challenges.

3) Multi-objective EMS development should get more focus in future investigations because only the minimization of fuel consumption and tailpipe emission will certainly operate ICE around its best operating points but it might overexploit electric motors, battery and other cardinal components apart from ICE. Objectives such as minimization of battery health degradation, drivability optimization, electric motor longevity should be included in the overall cost structure.

4) With the rapid advancement of intelligent transportation systems (ITS), data-driven iEMS are escalating, becoming lucrative options to explore. Accessibility to traffic data, geographic road map, and road geometry makes the prediction based iEMSs more reliable and adaptive. Therefore, the future trend would be developing advanced data-driven iEMSs.

5) Cloud-based EMS is a significant progression that needs to be more investigated. An example of these kinds of EMSs can be the determination of the best possible vehicle trip information with the objective of minimum fuel consumption through a cloud-interaction system. In fact, cloud computing would generate the optimal route/velocity trajectory and the results would go back to the driver through a visual interface [117].

TABLE 2. Summary of Most Popular Controller Chips on the Market

	MCU/MPU	FPGA or SoC	GPU	DSP
Overview	Single or Multi-Core architectures with many peripherals already coded.	A collection of logical gate arrays that can be configured in the field.	Originally designed for graphics - Includes many parallel ALU cores.	Optimized processor for the specific application
Strengths	• Ease of programming • Versatility • Debug is simple	• Configured for a specific application • Can be re-programmed in field • Low power consumption • Parallelism of functions • Design can become ASIC design for high volumes • Determinism	• Very high computational performance • Fast video processing algorithms • IPs for DSP, ML and image processing	• Low price • Application specifically optimized
Weaknesses	• High power consumption • Sequential operations within core • Limited parallelism	• Difficult to program • Difficult to debug • Sequential operations are challenging	• High power consumption • Cannot perform certain algorithms • Application specific	• High power consumption • Cannot perform certain algorithms • Application specific
Suitable Domain Application in Electrified Vehicles	• Inter-domain HMI Interface • Inter-domain ADAS • Inter-domain Connectivity • Energy management systems • Supervisory/Domain Monitoring and Control	• Inter-domain ADAS • Motor control • Power electronics control • Sensor fusion • Battery management system • Inter-domain HMI Interface	• Sensor fusion • Inter-domain ADAS • Inter-domain HMI Interface • Camera vision interface	• Motor control • Power electronics control • Battery Management Systems • Connectivity

V. ENABLING TECHNOLOGIES

Intelligent methods introduced in Section III have been widely researched due to the advancements in technologies. With the cost and size of high computational platforms decreasing and the rise of high bandwidth communication increasing due to the availability of cheap computation platforms, the deployment of intelligent methods into xEVs is becoming more and more attractive. The aspect of hardware and software need to be mixed and both need to have a fail-safe requirement [118]. The primary enabler of technologies for the deployment of intelligent methods in commercial vehicles includes embedded controller chips, communication protocols, and connectivity functions, which are summarized in this section.

A. CONTROLLER CHIPS

The ECUs are used in conventional vehicle architectures utilize embedded 8, 16 and 32-bit processors with a clock frequency of 40 MHz. A 2 MB code is flashed and encrypted onto the ECU memory, usually a non-volatile memory (NVM), by the manufacturer [119]. Compared to personalized computers, these ECUs have very little computational power. This is the reason why there are a limited number of vehicle operations that can be contained inside an ECU. The number of ECUs have been increasing in vehicles due to the utilization of the same type of controller chip in the distributed architecture. Some specific ECUs have been implemented using a digital signal processor (DSP) for actuating or sensing a vehicle component signal.

By utilizing the technological advances in controller chips, many functions can be combined into a single but powerful ECU which is the trend of the DCA described in Section II-B. With the DCA and the ability of using intelligent algorithms, much more powerful ECUs need to be implemented as the domain controller such that a vehicle fail-safe operation is achieved. Furthermore, instead of having complex ECUs actuating or sensing signals from vehicle components, smart actuators/sensors will be used that can comprise of a simple but fast ECU. With these requirements and the writers' experience, the domain controllers and smart actuators/sensors ECU could be implemented using the following technologies that have garnered much attention in aerospace, data centers or servers, and machine learning or artificial intelligence industries [43]. Multi-core microprocessor unit (MPU), field programmable gate array (FPGA), and application specific integrated circuit (ASIC) can be used as domain controllers. Smart actuators/sensors include microcontroller unit (MCU), graphical processing unit (GPU), system-on-chip (SoC), ASIC, and digital signal processor (DSP).

A summary of the ECU main controller chips mentioned in this section can be found in Table 2. As described previously, MCUs, MPUs and mainly DSPs are used in today's vehicles. Some exceptions do include using SoCs for local interconnect network (LIN) communication-based slave nodes or ASICs for specific types of communication protocols that would alleviate the burden of computational resources on ECUs [118]. To move to a future centralized computational platform that includes all domain functionalities or even all vehicle functionality, safety will be paramount to the integration of these technologies. The ISO26262-part 5 has been an integral part of the development and introduction of complex electronic hardware into these new E/E architectures. The reason for this is these new electronics must perform safety critical functions such as steering, accelerating and braking so if a component fails, it has to do so in a fail-safe manner. Functional safety must remain a top priority while introducing these new technologies.

B. IN-VEHICLE COMMUNICATION PROTOCOLS

The requirement of increased bandwidth has put in-vehicle communication protocols at the front of the new E/E architecture design to ensure reliability and safety are taken into consideration when adding new sensors and combining ECU functions together. This is due to the increasing number of electrical components that need to communicate with each other to ensure appropriate functionality [40]. Furthermore, the complication of including legacy devices and code has put challenges to the introduction of new E/E architectures

TABLE 3. Summary of Possible Inter-Domain and Gateway Communication Protocols for Domain Control Oriented E/E Architecture

	CAN-FD	FlexRay	LIN	MOST	LVDS	Automotive Ethernet
Bandwidth	1-10Mb/s	20Mb/s	20kb/s	150Mb/s	655Mb/s	1Gb/s
Strengths	• Robust • Low Cost • Supports distributed controls	• Fault Tolerant • Time Triggered (Similar to TTCAN) • Supports distributed controls	• Robust • Low Cost • Simplistic	• Robust • Optimized for images and networks • MOST25/50 can be optically driven	• General • Internal IP's can be generated.	• TCP/IP integration • High Bandwidth • Robust • Supports distributed controls
Weaknesses	• Obsolescence	• Obsolescence • Medium Cost	• Low bandwidth • Single failure point • Obsolescence	• High Cost • Complex • Extra hardware needed	• Extra hardware needed • Complex • Signal integrity is needed	• Complex • High cost • Extra hardware needed
Suitable application in Electrified Vehicles	Inter-domain safety critical applications and/or redundancy	Inter-domain ADAS and safety critical applications	Inter-domain HMI Interfaces and Body	Sensor fusion, Infotainment and redundancy	Inter-domain ADAS and safety critical applications	Gateway communication, ADAS and Inter-domain Connectivity

since many communication protocols are currently included in conventional distributed architectures.

Up until recent years, the main communication protocol inside of vehicles has been the controller area network (CAN) developed by Robert Bosch GmbH in 1986 [120]. The CAN protocol has been attractive for manufacturers due to its ability to be flexible, low cost, and scalability. Newer CAN protocols, such as the CAN flexible data rate (CAN-FD), have tried to increase the bandwidth from 1 Mb/s all the way up to 10 Mb/s for some instances [43].

FlexRay has been introduced by the consortium of BMW, Daimler Chrysler, Philips Semiconductors, Motorola and Bosch [120]. It is a network communication that has been introduced to enable the safety critical “X-By-wire” applications such as steering, throttle, braking and many more [40]. Flexray offers time-triggered communications, synchronized global time-frame and a real-time data transmission by using a time division multiple access (TDMA) technique which is a requirement for safety critical functions such as “X-By-wire” technologies where no mechanical link is present in case of failure [121].

Other communication protocols include low voltage differential signal (LVDS), LIN and media oriented systems transport (MOST). LVDS communication has been widely used in many applications such as industrial, aerospace, telecom and as well in Automotive. LVDS comprises of a serial communication working in complimentary pairs to ensure the common mode noise is removed from the lines. This makes this communication robust but complex to implement as the length of the wires are the bottle neck of this application due to having a minimum of two wires for differential signals. LIN was introduced in 1998 to use in applications to supplement CAN protocol where cost is critical and the bandwidth is low [122]. It consists of a single wire and a low cost solution for simple actuation and sensing [120]. LIN is typically used for vehicle door, seat and temperature control devices. MOST has been introduced by MOST cooperation in 1998 [120]. MOST works well with any type of media such as video, audio, radio and more. The communication medium has been through optical fibers and can support up to 64 nodes in a ring topology [121].

Automotive Ethernet (AE) is a promising solution for solving the bandwidth problems related to data and being able to perform sensor fusion easily. AE has been a promising solution due to its similarity to normal Ethernet that has been used as the local area network (LAN) for most computers and day-to-day lives [43]. The wide acceptance of the Ethernet protocol has been the main driver in using AE in transportation vehicles [43]. In terms of fail-safe criteria, the Ethernet protocol includes many standards up-to-date that ensure the safe communication between Ethernet nodes. One disadvantage of using AE is that a switch node Ethernet device would need to be used. With the advancements in controller technologies described in Section V-A, this would not be a problem as many functions can be integrated into one ECU along with an AE input decoder. A summary of the communication protocols mentioned can be found in Table 3.

C. CONNECTIVITY

The concept and contents of vehicle connectivity have significantly expanded and have enabled a whole new world for the electric car to be designed in. Some of the key applied technologies involved in the connectivity impact of the E/E architecture are listed below [123]:

- WiFi
- Cellular Network
- Global Navigation Satellite System (GNSS)
- V2X (Vehicle-to-Vehicle, Vehicle-to-Grid, etc.)
- Dedicated Short-Range Communications (DSRC)
- Over-The-Air (OTA) updates

With these types of technologies, external communication of the vehicle can be manifested much easier than before. This brings in added safety with the added “nodes” that can communicate with the vehicle. Such nodes can be smart traffic lights, buildings, houses, cellphones, power generation units that can communicate with each other to ensure all information is passed between each vehicle [43]. This will add additional constraints to the vehicle EMS such that they can become more efficient in real-life and can adapt to its environment stimulus.

VI. CONCLUSION

The present literature has aimed to introduce a novel categorization followed by a detailed discussion of iEMSs. The features which enable an EMS to be intelligent are listed, which is rarely seen in other review papers. Detailed explanations, advantages, disadvantages, and future research directions are presented for each method. The analysis of RL-based, ANNs-based, and markov decision problem-based EMSs are undertaken here, which leads to more profound insight into iEMSs. Composite iEMSs are studied as a new category, and they can be explored more in future research. More broadly, the review establishes an introduction to enabling technologies of implementing iEMSs.

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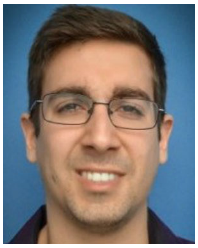

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