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A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics

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ABSTRACT

Hybrid electric vehicles (HEVs) are one of the most viable technologies to achieve the goals of energy saving and environmental protection before a breakthrough in battery technology and fuel cell technology. Energy management strategy as a key technology of HEVs is studied extensively and deeply to improve the performance of HEVs and speed up the industrialization of HEVs. This paper quantitatively analyzes and evaluates current research status of energy management strategies for HEVs based on bibliometrics for the first time, through content analysis involving analysis of author keywords and abstracts. Then qualitative analysis is performed for all kinds of energy management strategies that are used in HEVs in detail, essential characteristics involving pros and cons, interconnections and improvement potential among various energy management strategies are revealed from the view of control theory. Finally, latest developing trends in energy management strategies of HEVs are presented to improve the performance of HEVs based on above quantitative analysis and qualitative analysis, covering driving cycle recognition/prediction algorithms, integrated multi-objective, coordinated optimization energy management strategies, good balance between computation complexity and optimization performance of energy management strategies, fair and credible evaluation system of energy management strategies. This paper not only first provides a comprehensive analysis of energy management strategies for HEVs, but also puts forward the emphasis and orientation of future study, which will broaden relevant researchers' vision and promote the development of a simple and practical energy management controller with low cost and high performance for HEVs.

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1. Introduction

Energy saving and environmental protection have become two main themes of the world today. To overcome current energy limitations and environmental issues generated by vehicles, several approaches have been proposed by governments and scholars around the world, including limiting transportation activity, restricting automobile purchases, enacting strict emission regulations, improving fuel efficiency of conventional vehicles and developing new energy vehicles. Among all suggested solutions, restricting transportation activity and automobile purchases would hinder the development of industrial economy, and the potential for improving fuel efficiency of conventional vehicles is also limited, thus developing new energy vehicles is considered to be one of the most promising and practical solutions. That is why auto-manufacturers and researchers have put much effort into developing new energy vehicles.

There are mainly three types of new energy vehicles: purely electric vehicles (usually being referred to as battery electric vehicles-BEVs), fuel cell electric vehicles (FCEVs) and HEVs [1]. Though BEVs and FCEVs are believed to be the cleanest automobiles without using fossil fuel in the future, the development of BEVs and FCEVs is influenced by battery technology and fuel cell technology respectively, as well as charging infrastructure and hydrogen infrastructure. Limited by the safe, lifetime, purchasing cost and energy/power density of battery packs and fuel cells, and the unavailability of desired infrastructure, BEVs and FCEVs will not likely be ready for mass production in the next few years. HEV generally uses an electric motor (EM) powered by an energy storage system (ESS) along with a downsized internal combustion engine (ICE) powered by fossil fuel. It is therefore considered as an in-between product for the transition from conventional vehicle to future clean vehicle. HEV combines benefits of BEV and conventional vehicle, such as long driving range, good power performance, convenient refueling, low emission and noise. Therefore, before a great breakthrough in battery and fuel cell technology, due to great potential to reduce fuel consumption and pollutant emissions, HEV has become one of the most viable technologies to achieve goals of energy saving and environmental protection in the short to medium term, thus attracting great attention from auto-manufacturers and research institutions.

HEV is a typical complex electro-mechanical-chemical system, integrating electrical, mechanical, chemical and thermodynamic systems. The transfer, transform, and evolution of complex power flow, energy flow and information flow occur when HEV is in motion. Therefore, the potential of energy saving and emission reduction for HEV is decided by mechanical connection way of components and instantaneous power split law between ICE and EM, namely, depends on configuration and energy management. HEV's configuration is the basis of energy management, which determines algorithm selection of energy management and optimization potential. The system's configuration includes the selection of system topology and parameter design of major components. Based on mechanical architecture, HEV powertrain configuration can be generally classified into three types: series, parallel, and power-split (series–parallel). Every configuration has its own advantages and disadvantages. The selection of configuration is usually dependent on customer requirements. As a result, main challenge for HEV is how to split the power in an optimal manner while delivering desired performance under system constraints. For the past decades, numerous attempts have been made to design effective energy management strategies. Energy management has become one of most extensive research topics in HEVs so far.

The existing energy management strategies of HEVs can be mainly classified into rule-based energy management strategy and optimization-based energy management strategy. Both types of energy management strategies have been extensively studied by many scholars, and research contents involves various aspects, including state-of-the-art of energy management strategy, general formalization of energy management problem, characteristics and control effects of different energy management strategies, effect factors of energy management strategies, relations and differences among different energy management strategies. The state-of-the-art, classification, pros and cons of various energy management strategies applied in HEVs were described in [2–7]. An innovative four-step method for designing optimal energy management strategy was introduced in [8] while a unified approach to describe energy fluxed within HEVs was presented in [9]. A general formulation of energy management problem for HEVs and plug-in HEVs (PHEVs) was proposed in [10]. Fundamental structural limitations of rule-based energy management strategy were discussed by Opila et al. [11]. Optimization techniques and their implementation methods used in energy management of HEVs were illustrated in [12]. The characteristics and control effects of various energy management strategies were deeply compared and analyzed, involving the comparison between power split and torque split energy management strategy [13], the comparison between rule-based and global optimization-based energy management strategy [14–15], the comparison between deterministic logic and fuzzy logic energy management strategy [16–19], the comparison between rule-based energy management strategy and equivalent consumption minimization strategy (ECMS) [20–21], the comparison between stochastic dynamic programming (SDP) and ECMS [22], the comparison among electric assistant energy management strategy, adaptive energy management strategy and genetic algorithm (GA) [23], the comparison among parallel electric assistant, adaptive and fuzzy logic energy management strategy [24], the comparison among rule-based energy management strategy, adaptive equivalent consumption minimization strategy (A-ECMS) and H_∞ energy management strategy [25], the comparison among dynamic programming (DP), Pontryagin's minimum principle (PMP) and ECMS [26], the comparison among all electric-charge sustaining (EV-CS), charge depleting–charge sustaining (CD–CS) and blended energy management strategy for PHEVs [27–32]. The relations between different optimization-based energy management strategies were also revealed, such as adaptive equivalence strategy and mixed integer quadratically constrained linear program (MI-QCLP) [33], DP and ECMS [34], DP and PMP [35–36]. The effect factors of energy management strategies covered intelligent transportation system (ITS) [37], terrain preview [38] and noise factors [39].

There have been a small number of literature surveys on energy management strategies of HEVs, and the existing review papers focus on analyzing the development of energy management strategies and comparing several energy management strategies qualitatively. However, there has been no scholar presenting a comprehensive overview of all types of energy management strategies developed for energy management control of HEVs from both quantitative and qualitative view. This study tends to fill this gap. By means of bibliometrics, quantitative description of current research situation in the field of energy management strategies for HEVs is presented first. Then, from the view of control theory, qualitative analysis is carried out to reveal essential characteristics, interconnections and improvement potential of various energy management strategies. Finally, based on quantitative and qualitative analysis results, research focus and the trend of development of energy management strategies for HEVs are identified.

This paper is organized as follows. After this introduction, major research method adopted by this study is introduced briefly in Section 2. The current research status of energy management strategies for HEVs based on quantitative analysis is presented in Section 3. From the point of qualitative view, essential characteristics, interconnections and improvement potential of various energy management strategies are revealed in Section 4. Latest developing trends in energy management strategies of HEVs are discussed in Section 5. Finally, significant results are summarized in Section 6.

2. Methodology and data collection

Bibliometric analytical technique is a method to quantitatively analyze academic literature using mathematical and statistical techniques, which has been widely used in various disciplines [40]. Bibliometric analysis methods include temporal analysis, geographic analysis, and content analysis [41]. According to the number of publications, authors and citations, temporal bibilometric analysis usually focuses on the development of research areas across different stages. Based on publication outputs by countries and institutions, geographic analysis displays global distribution of research areas. Different from temporal and geographic analysis, content analysis aims to identify current hotspots on the basis of the frequency of author keywords and subject distribution. This study is concerned with present status and future developing trends; therefore, only content analysis covering author keywords analysis and abstracts analysis is conducted to give a quantitative description of development status for energy management strategy, as described in Section 3. Based on content analysis results, qualitative analysis of rule-based energy management strategy and optimization-based energy management strategy based on control theory is made to present focus and difficulties of energy management strategy for HEVs, involving essential characteristics, interconnections and improvement potential of various energy management strategies. Future developing trends of energy management strategy for HEVs are derived from quantitative and qualitative analyses.

All documents employed in this study were from databases of Science Citation Index Expanded (SCI-EXPANDED) and Conference Proceedings Citation Index-Science (CPCI-S), based on ISI Web of Science, Philadelphia, PA, USA. In this study, only documents published from 1998 to 2014 were discussed due to few articles regarding energy management strategies of HEVs prior to 1998. HEVs presented in this paper did not include fuel cell HEVs and hybrid solar vehicles. In order to find all documents in the field of energy management strategies for HEVs as completely as possible, hybrid search method combining computer search and manual search was adopted. First, terms such as hybrid electric vehicle, hybrid powertrain, hybrid electric car, hybrid electric bus, hybrid electric truck and hybrid electric automobile were used as keywords to search in the categories of title/keywords/abstract based on SCI-EXPANDED and CPCI-S. The document types were limited in articles, proceedings papers and reviews. Then, based on the result of computer search, there were a total of 575 documents related to energy management strategies of HEVs through manual search furthermore.

In summary, employed research method and framework of this study is shown in Fig. 1.

3. Quantitative analysis of energy management strategy for HEVs based on bibliometrics

3.1. Analysis of author keywords

Among 575 articles, 373 articles have provided author keywords, accounting for 64.9% of total articles. An analysis of author keywords is conducted to identify research focus in energy management strategy for HEVs. There are a total of 697 unique author keywords for 373 articles proposed by authors, which appear 1749 times. The frequency of author keywords and their ranks follows the power law distribution as shown in Fig. 2, indicating that the majority of author keywords are

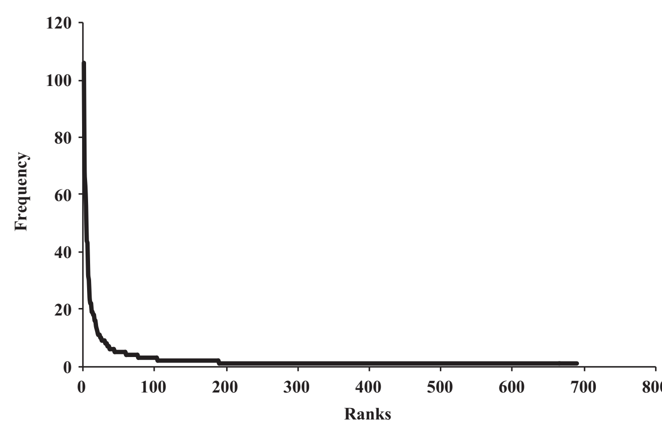

Fig. 2. The power relationship between the frequency and ranks of author keywords.

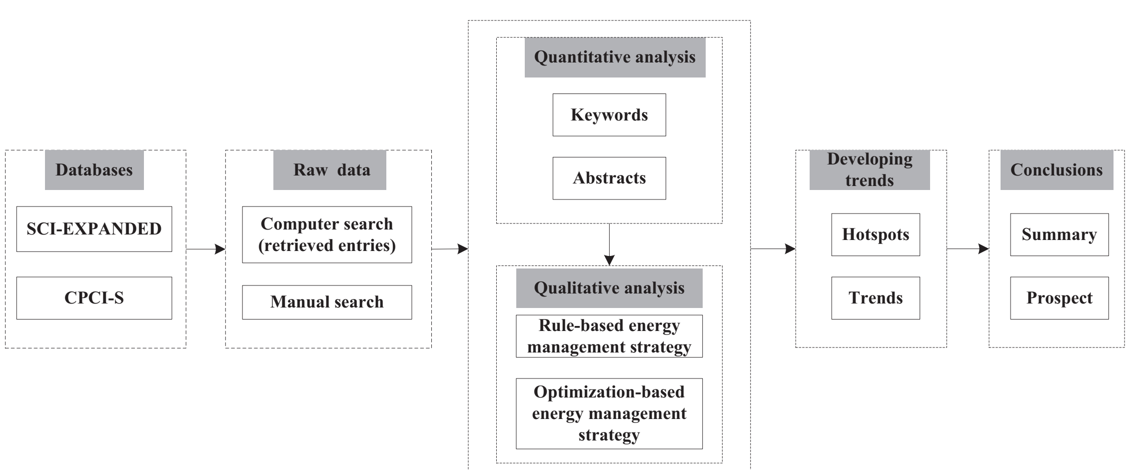

Fig. 1. Research method and framework.

not used frequently and only a small number of author keywords are widely employed. 508 author keywords only appear one time, which account for 72.9% of these 697 author keywords. Nevertheless, the 25 (3.6%) most frequent author keywords appear 708 times and occupy 40.5% of total occurrences for author keywords. Based on the analysis of total author keywords, we can find that many different author keywords mean the same idea. As a consequence, it is necessary to make co-words clustering analysis for identifying current research directions and hotspots of energy management strategies for HEVs. Traditional hierarchical clustering algorithm is sensitivity to the frequency of author keywords and may not cover all related research subject. Due to the above drawbacks, a new improved hierarchical clustering algorithm is proposed as follows.

The research is usually composed of objects, purposes, methods and contents of the study. For this reason, in this new clustering algorithm, author keywords involving above four aspects are considered as co-words. By this way, the clustering algorithm is not sensitive to the frequency of author keywords. Then, based on our expertise and experience, for energy management strategy of HEVs, all co-words are classified into four types, and the frequency of author keywords in each type is obtained by our own statistical analysis software. As shown in Fig. 3, HEV is main research object including series HEV, parallel HEV, series–parallel HEV and PHEV. The research purpose is to improve fuel economy, reduce emissions and ensure drivability of HEVs. Simulation and modeling as two main methods are utilized to study energy management and optimal control of HEVs for realizing above mentioned goals. By comparing the frequency of different types of co-words, it is revealed that: (1) PHEV attracts more attention; (2) researchers are more concerned with fuel economy than emissions of HEVs while few researchers focus on drivability of HEVs; and (3) specific energy management strategies have been widely studied. In order to understand different kinds of energy management strategies further, clustering analysis of co-words in specific energy management strategies is also made as described in Fig. 3. DP and fuzzy logic control are the two most widely used energy management strategies, followed by GA, PMP, model predictive control (MPC), neural network (NN) and ECMS. The other energy management strategies include rule-based control, particle swarm optimization (PSO), robust control, stochastic optimal control, evolutionary algorithm (EA), support vector machine (SVM), convex optimization, bees algorithm (BA), direct method, machine learning, simulated annealing (SA), quadratic programming (QP), simplex method, shooting method, extremum seeking (ES), game theory (GT), parallel chaos optimization algorithm (PCOA), Dividing RECTangles algorithm (DIRECT), varying-domain optimization and so on.

Although analysis results of author keywords can reflect current research focus to some extent, 35% of total articles still have no author keywords. Moreover, some author keywords are not relevant to the subject of the article. Given that, abstracts analysis of articles is necessary for further understanding subjects of articles, which will be described in the following section.

3.2. Analysis of abstracts

Through reading and analyzing abstracts of these 575 articles carefully, research subjects of all these articles can be categorized into three main research fields as shown in Fig. 4 (a) review and comparative analysis of energy management strategy; (b) rule-based energy management strategy; and (c) optimization-based energy management strategy. Rule-based energy management strategy can be classified as deterministic rule-based energy management strategy and fuzzy rule-based energy management strategy according to characteristics of used rules, while optimization-based energy management strategy can be classified into global optimization energy management strategy and real-time optimization energy management strategy based on employed information level of driving conditions. On the basis of solving methods of optimization control problem, global optimization energy management strategy and real-time optimization energy management strategy applied in the energy optimal control of HEVs can be divided into different subcategories, as shown in Fig. 5. According to statistical analysis, quantity distribution of various types of energy management strategies is displayed in Fig. 6.

As described in Fig. 4 and Fig. 6, optimization-based energy management strategy has received more attention from scholars than rule-based energy management strategy. DP, PMP and stochastic search methods are top three types of global optimization energy management strategies while ECMS, MPC and intelligent control are the three most widely studied real-time optimization energy management strategy. Although rule-based energy management strategy cannot obtain the optimum as optimization-based energy management strategy, it still gains a certain concern due to easy implementation. In order to acquire the development trends of above most widely used energy management strategies, temporal analysis of these strategies is made as shown in Fig. 7. From Fig. 7, it is clearly seen that: (a) the study on rule-based energy management strategy is continuing over the past years; (b) for global optimization energy management strategy, on one hand, DP has gained great development since 2007 while PMP is widely studied from 2011; on the other hand, the research on stochastic search method is conducted for many years, especially in 2006, 2009 and 2014; and (c) for real-time optimization energy management strategy, ECMS and MPC have obtained rapid development since 2009, while intelligent control is employed almost every year with relatively few occurrences. Generally speaking, rapid and tremendous development of energy management strategy for HEVs begins around 2009.

Above analysis of author keywords and abstracts shows development status and focuses from the quantitative point of view; yet, it does not propose any development difficulties or offer corresponding solutions. Furthermore, based on only quantitative analysis results, specific and complete development trends as well as control effects of different energy management strategies cannot be derived. Therefore, qualitative analysis of various energy management strategies is necessary. In this study, essential characteristics involving advantages and disadvantages, interconnections and improvement potential of total employed energy management strategies are analyzed and compared. The details are as follows.

4. Qualitative analysis of energy management strategy for HEVs based on control theory

The qualitative analysis is based on above quantitative analysis, focusing on rule-based energy management strategy and optimization-based energy management strategy. First, various subtypes of applied deterministic rule-based and fuzzy rule-based energy management strategies are analyzed and characteristics of rule-based energy management strategy are generalized. Second, various subtypes of employed global optimization and real-time optimization energy management strategies are discussed and characteristics of optimization-based energy management strategy are summarized. Finally, comparative analysis between rule-based energy management strategy and optimization-based energy management strategy is performed.

4.1. Rule-based energy management strategy

4.1.1. Deterministic rule-based energy management strategy

Deterministic rule-based energy management strategies can be sub-divided into thermostat (on/off) strategy, power follower

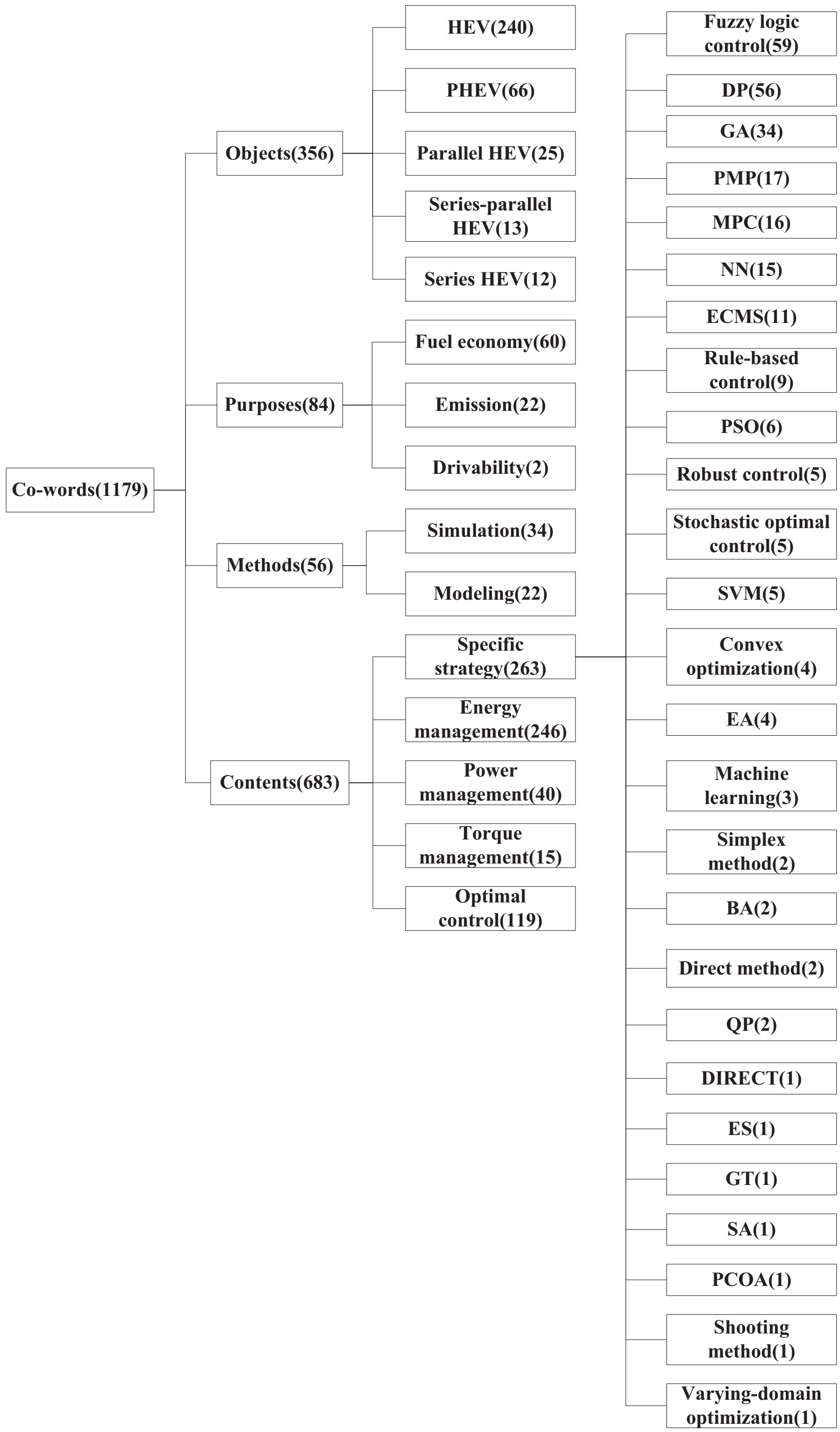

Fig. 3. Co-words distribution.

(baseline) strategy, engine optimal working point strategy, engine optimal operation line strategy, engine optimal efficiency region strategy, system optimal operation point strategy and frequency-based strategy.

In the thermostat strategy, ICE operates at its highest efficiency point once it turns on, while battery SOC is always maintained between its preset upper and lower bounds by turning on or turning off ICE. Although the thermostat strategy provides best efficiency for the engine-generator set, overall system efficiency of HEV is low. Furthermore, the battery pack requires high performance to satisfy power demands under various operating conditions. Therefore, the thermostat strategy is mostly used in series HEVs [42]. The power follower strategy uses ICE as main power source, ICE works along its optimal working curve as much as possible while EM is used to provide additional power and sustain battery SOC. Compared to the thermostat strategy, the power follower strategy improves overall system efficiency and the durability of the battery pack and other electrical components. The power follower strategy is applicable to parallel HEVs and series–parallel HEVs [43]. In order to overcome the weakness of thermostat strategy and power follower strategy, hybrid thermostat strategy combining thermostat strategy and power follower strategy is proposed to improve fuel economy further for series HEVs [44]. Frequency-based strategy splits power demand into low and high frequency components by low-pass filtering incorporated with load-leveling, which is mainly applied in series HEVs. Compared with the thermostat strategy, it can improve fuel economy, decrease emissions and increase battery life simultaneously [45].

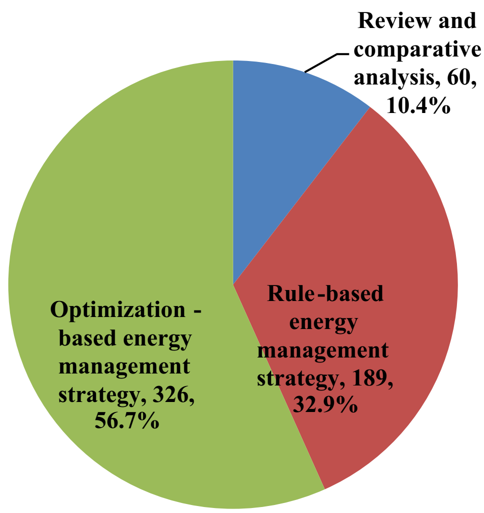

Fig. 4. Distribution of research subjects.

Due to special powertrain components of series–parallel HEVs such as planetary gear set and continuously variable transmission (CVT), the operating point of ICE can be adjusted freely. So engine optimal working point strategy [46], engine optimal operation line strategy [47] and engine optimal efficiency region strategy [48] are proposed for series–parallel HEVs. The engine optimal working point strategy adopts EM to provide additional power due to good dynamic characteristic of EM, while keeping ICE working at its optimal working point. The engine optimal operation line strategy is similar to the above power follower strategy, and ICE will always work along optimal operation line unless required current exceeds the limits of battery packs or EM. The engine optimal efficiency region strategy is also called power-balancing strategy, where ICE is kept to operate in optimal efficiency region. Considering transmission energy loss, system optimal operation point strategy combining ICE optimal operation line and the maximization of transmission efficiency is introduced to further improve the performance of series–parallel HEVs [49].

Deterministic rule-based energy management strategy is usually implemented using state machine logic. Although it has been successfully used in commercial HEVs, like Toyota Prius, due to fixed rules, it lacks the flexibility to different driving cycles and the ability to deal

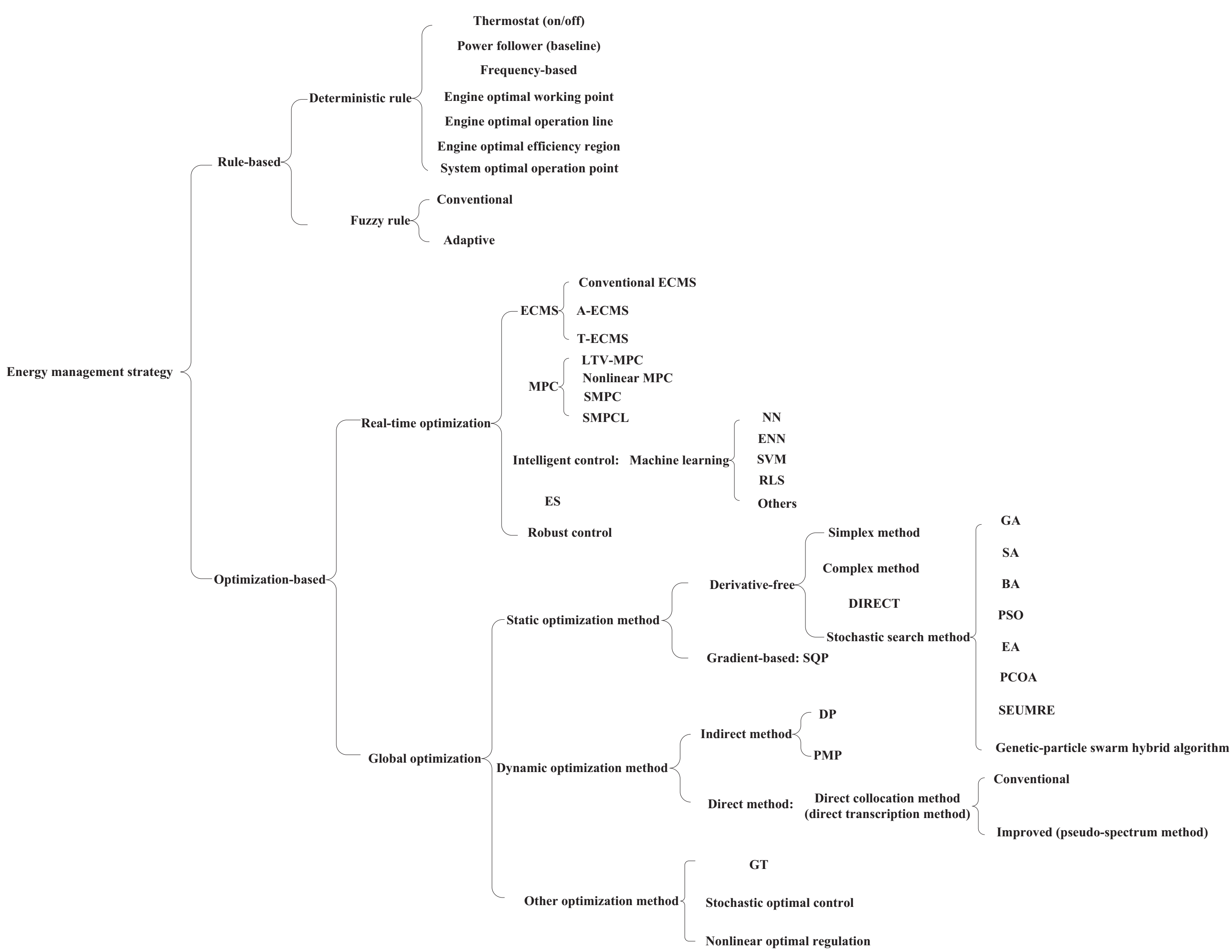

Fig. 5. All kinds of employed energy management strategies.

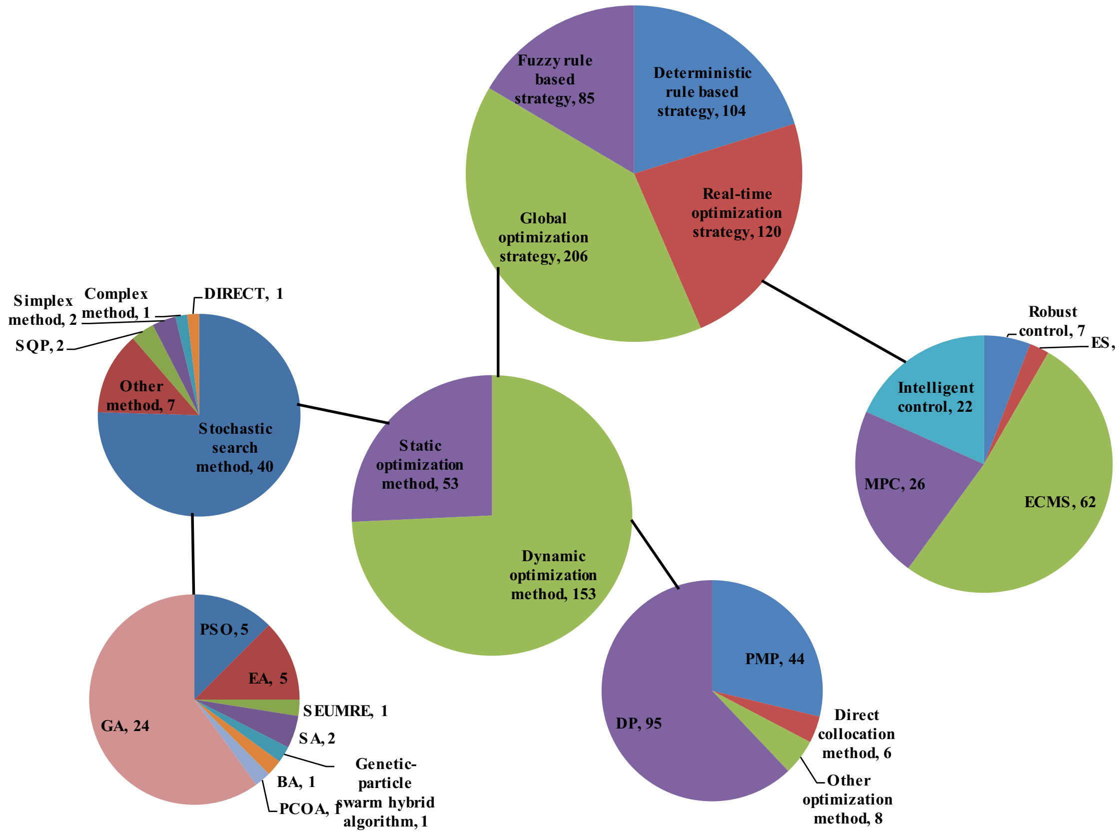

Fig. 6. Quantity distribution of various types of energy management strategies.

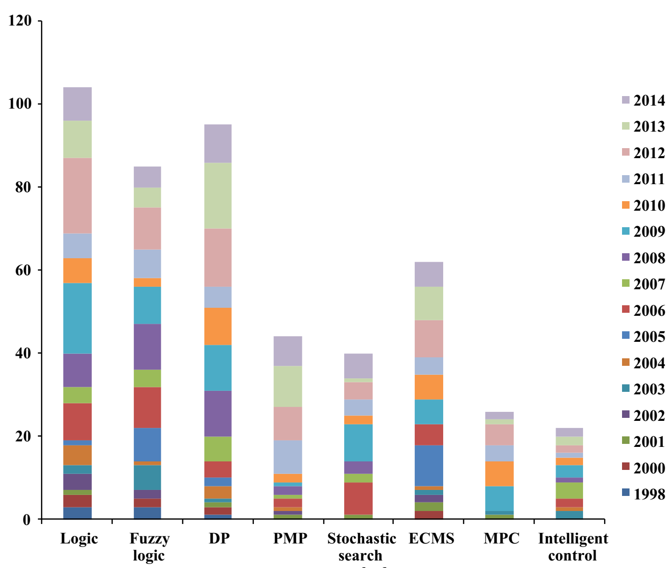

Fig. 7. Temporal distribution of most widely used energy management strategies.

with uncertainty caused by model errors of the powertrain. Consequently, both driving cycle recognition [50] and driving cycle prediction [51] are introduced to deterministic rule-based energy management strategy.

4.1.2. Fuzzy rule-based energy management strategy

Fuzzy rule-based energy management strategy is an extension of deterministic rule-based energy management strategy. The basic idea of such strategy is to formulate a collection of fuzzy IF-THEN rules from human knowledge and reasoning, which offers a qualitative description of controlled system. So the dependence of deterministic rule-based energy management strategy on precise mathematical model of controlled system is removed. The main advantages of fuzzy rule-based energy management strategy are its robustness to measurement noise and component variability as well as its adaption. As a result, fuzzy rule-based energy management strategy is very suitable to multi-domain, nonlinear, time-varying systems such as HEVs. As pioneers of fuzzy rule-based energy management strategy, Baumann et al. [52], Lee and Sul [53] propose a fuzzy rule-based torque control strategy for parallel HEVs as early as 1998. Then, fuzzy rule-based energy management strategy is also applied to series HEVs [54], series–parallel HEVs [55].

Fuzzy rule-based energy management strategy is generally composed of five parts: input quantization, fuzziness, fuzzy reasoning, inverse fuzziness, and output quantization. Fuzzy reasoning consists of membership function and fuzzy rule, which determines control performance of fuzzy rule-based energy management strategy. However, membership function and fuzzy rule are usually derived from human's experience and intuition, thus good control performance cannot be guaranteed. In order to improve fuel economy and emission further, a proportional factor method [56], GA [57], PSO [58], and BA [59] are utilized to optimize membership function or fuzzy rule. However, the above optimization process is based on a specific driving cycle. To further improve the robustness and adaptability of fuzzy rule-based energy management strategy, adaptive neural fuzzy inference system (ANFIS) [60], machine learning algorithm such as LOPPS [61], and driving cycle recognition [62–63] are introduced to fuzzy rule-based energy management strategy for improving its robustness to the change of driving cycle, while compensation fuzzy neural network (CFNN) is employed to improve self-adaptive ability of fuzzy rule-based energy management strategy [64].

4.1.3. Characteristics of rule-based energy management strategy

Based on the above analysis, rule-based energy management strategy is a real-time energy management strategy in which a set of rules are designed based on human expertise, heuristics, engineering intuition and powertrains characteristics. Such a type of energy management strategy is computationally efficient and easy to implement, which has been widely used in prototypes and commercial HEVs. The control performance of rule-based energy management strategy depends on employed thresholds and rules. However, accurate thresholds and rules are difficult to define due to the lack of mathematical analysis and theoretical basis. Extensive calibration and tuning of the parameters are required to improve the performance of given vehicle configuration over a specific driving cycle. Therefore, the development of rule-based energy management strategy is time-consuming, vehicle-dependent, and driving cycle-dependent. Furthermore, any minimization or optimization is not involved in this kind of energy management strategy, the optimality of the solutions cannot be guaranteed. Various techniques have been proposed to optimize the performance of rule-based energy management strategy, such as blending energy management strategy composed of rule-based energy management strategy and instantaneous energy management strategy [65], hybrid energy management strategy combining rule-based energy management strategy and ECMS [66], extracting efficient thresholds and rules from optimization-based energy management strategy such as DP [67] and PMP [68].

4.2. Optimization-based energy management strategy

4.2.1. Global optimization energy management strategy

The energy management strategy based on global optimization technique is to get global optimum by minimizing a cost function representing fuel economy and/or emissions along a given driving cycle, as well as considering physical constraints from ICE, ESS and EM. This technique relies on a-priori knowledge of driving cycle, so it is also called as a non-causal control approach. Unless future driving condition can be predicted during real-time operation, this kind of energy management strategy cannot be implemented directly. Furthermore, computational burden of global optimization energy management strategy is larger than that of rule-based energy management strategy. Despite of preview nature and computational complexity, global optimization energy management strategy is still the most studied energy management strategy of HEVs as shown in Fig. 5.

In view of optimization control problem of HEVs, there exist three main solution methods. The first one optimizes strategy parameters of a rule-based energy management strategy, thus energy management problem becomes a parameter optimization problem, also called a static optimization problem, and the optimum can be obtained via static optimization methods. The second one formulates energy management problem of HEVs as a dynamic, nonlinear, and constrained optimization problem, also known as an optimal control problem. Such problem can be solved by dynamic optimization methods. The third one simplifies optimal control problem of HEVs with model approximations as mathematical programming problem, such as sequential quadratic programming problem [69], quadratic programming problem [70], mixed integer linear programming problem [71–72], and convex programming problem [73]. The mathematical programming problem can also be solved by means of static optimization methods. Both static optimization methods and dynamic optimization methods that have been utilized in optimization control problem of HEVs are explained in detail below.

4.2.1.1. Dynamic optimization method. The solving methods of optimal control problem generally can be classified into three types: indirect methods, direct methods and other methods. Indirect methods are based on optimal control theory, including calculus of variations, PMP and DP; while direct methods approximate optimal control problem as static optimization problem by discretization, and solve such problem using the same method as for solving static optimization problem. Other methods refer to some new solving methods except direct methods and indirect methods.

4.2.1.1.1. Indirect methods. The calculus of variations requires that admissible control set of optimal control problem is an open set and optimized functions are continuously differentiable, which limit its application in optimization control problem of HEVs. Both DP and PMP have been widely used in the development of global optimization energy management strategy, as described below.

4.2.1.1.1.1. DP. DP was proposed by Bellman in the 1950s to solve optimal control problems for nonlinear dynamical systems. DP decomposes dynamic optimization problem into a sequence of sub-problems by discretizing original optimization problem over time, thus forming a cost-to-go function at each sample time. Optimal control schedule can be obtained by solving sub-problems backwards. So DP requires priori knowledge of entire driving cycle, also known as deterministic DP (DDP). Due to nonlinear characteristics of the powertrain for HEVs, DDP has to be solved numerically by approximations. The most popular approximation ways are quantization and interpolation. Therefore, both optimality and computational load of DDP are directly related to grid density, there is a tradeoff between optimality and computational load. Although the dependence on driving cycle and the well-known “curse of dimensionality” have limited DDP's application in a real-time control system of HEVs, global optimality derived from DDP has attracted many researchers' attention in the field of HEVs.Since Lyshevski et al. [74] first apply DDP to optimal energy management of series HEVs in 1998, DDP has been widely applied to optimization control for various types of HEVs, covering parallel HEV [75], power-split HEV [76], and PHEV [77]. DDP is usually employed to extract simple, implementable and optimal rules for a rule-based energy management strategy [75], or assess maximum performance of HEVs [78]. Although some feasible rule extraction methods have been proposed [79–80], the rule extraction process is generally time consuming; moreover, extracted rules are only suitable for a specific driving cycle.To overcome above drawbacks of DDP, Lin et al. [81] first propose SDP energy management strategy. This approach adopts a Markov process to represent power demand from the driver, thus optimal solution over a family of driving cycles rather than a given driving cycle can be obtained. Because it is formulated as an infinite-horizon optimization problem, the control law derived from SDP is a time-invariant state feedback and thus can be directly implemented in real-time control system. However, there are still some drawbacks for SDP-based energy management strategy. First, state transition probabilities of Markov process depend on driving cycles under consideration. Therefore, SDP only can obtain optimal solution under given Markov chain, at the same time control performance of SDP will be inferior to that of DDP for given driving cycle. Second, SDP problem is usually solved via value iteration or policy iteration, thus computation time is huge. Finally, the cost function of SDP discounts future cost and assigns a penalty to ESS's SOC deviation, thus two tunable parameters are introduced, namely discount factor and SOC deviation penalty.Based on aforementioned weakness in SDP-based energy management strategy, Tate et al. [82] first use shortest path stochastic dynamic programming (SP-SDP) to design HEVs' energy management strategy. SP-SDP is a specific formulation of SDP, which allows infinite horizon optimization problems to be addressed without the use of discounting (a discount factor in the cost function assures convergence by weighting future costs exponentially less than current costs). Without a discount factor, SP-SDP can realize advantages of SDP based energy management strategy with better SOC control and fewer parameters to tune. Afterwards, Opila et al. [83–84] design a SP-SDP based energy management strategy for a series–parallel HEV considering both fuel economy and drivability; whilst Moura et al. [85] develop a battery health-conscious energy management strategy by applying SP-SDP.To reduce computational burden and dependence on future driving cycles of DP, various improved algorithms based on DP are introduced. Fast dynamic programming (FDP) [86], neuro-dynamic programming (NDP) [87], iterative dynamic programming (IDP) [88], boundary-line DP [89], two-scale DP [77], multi-rate DP [90], and hybrid optimal energy management strategy combining DP and classical control theory [91] are proposed to improve computational efficiency. Furthermore, an online learning energy management strategy that composed of SDP and temporal difference (TD) method is also employed to improve the robustness to varying driving cycles and lower computational cost simultaneously [92]. However, the accuracy of improved DP-based algorithms is relatively poor.

4.2.1.1.1.2. PMP. PMP is another optimal approach based on optimal control theory that can be used to solve constrained global optimization problem, which is the extension of calculus of variations. PMP reduces constrained global optimization problem into local Hamiltonian minimization problem. As a result, PMP can be used in real-time control theoretically with less computation load than DP. PMP was first introduced to energy management control of HEVs in 2001 by Delprat et al. [93]. However, PMP only produces necessary but not sufficient conditions for an optimal solution, sufficient conditions only can be satisfied in special cases [94]. The major benefit of PMP is that initial costate is sole calibration parameter over a specific driving cycle, which has considerable influence on battery state. The optimal value of initial costate can be computed by an iterative process such as a simple dichotic search [95] if and only if future driving cycle is available in advance. Yet, in true driving environment, full knowledge of driving cycle cannot be known in advance. Moreover, initial costate is related to driving cycle, different driving cycles require different optimal values of initial costate. Both these limits present a challenge for real-time implementation of PMP. Various techniques have been proposed to estimate real-time initial costate as described below.Due to close relation between initial costate and battery state, the first approach computes real-time initial costate via correcting initial guess costate with feedback control on the error between actual battery SOC or state of energy (SOE) and reference battery SOC or SOE that derived from past, present or future driving information. The feedback control can be proportional (P) feedback control [96], or proportional integral (PI) feedback control [97], or proportional integral differential (PID) feedback control [98], or other nonlinear feedback control [99]. However, this kind of approach has good adaption to different driving cycle only if reference battery SOC or SOE is from future driving information, at the same time, the feedback coefficients and initial guess costate should be calibrated. In order to overcome the above disadvantages, the second approach is based on future driving condition from driving cycle prediction [100–102] or driving cycle recognition [103]. For driving cycle prediction, the driving information is collected from global position system (GPS) or ITS. The optimal value of initial costate is approximated on the basis of effective SOC drop rate and effective mean required power in [100] while it is estimated based on cruise time and available regenerative energy in [101]. Different from the methods proposed by [100] and [101], Boehme et al. [102] and Kim et al. [104] determine initial costate by solving a simplified optimal control problem with indirect variation of extremals such as dampened Newton-method and a shooting method with multiple initial conditions based on Newton-Raphson method. Except for the estimation of initial costate, the discrepancy between computation load of PMP and computational power of the vehicle controller also limits the application of PMP on real-time control system. Generally the look-up table is a good solution to the limits of storage capacity and computational power for the vehicle controller, which has been used to implement PMP online [102]. However, the size of the table will grow exponentially with the number of dimensions. Therefore, approximate PMP (A-PMP) is introduced by Hou et al. [105]. In A-PMP, based on piecewise linear approximation of engine fuel rate, instantaneous Hamiltonian optimization problem is simplified to convex optimization problem that can be implemented in the vehicle controller.

4.2.1.1.2. Direct method. Direct methods approximate an optimal control problem to a static optimization problem by discretization, so approximate optimal solution can be obtained by solving corresponding static optimization problem. Direct methods mainly consist of two kinds: control variable parameterization methods and direct collocation methods (also called as direct transcription methods). The big difference between both methods is that only control variables are discretized in control variable parameterization methods while both control variables and state variables are discretized in direct collocation methods. Due to difficulty in dealing with inequality constraints, control variable parameterization methods are not suitable for solving optimal control problems of HEVs. So, only direct collocation methods are employed to solve optimal control problems of HEVs [106]. The accuracy of approximate optimal solution acquired by direct collocation methods depends on approximation quality of original functions. The smaller segments can improve the accuracy of the solution but lead to a larger amount of calculation. Moreover, approximation optimal solution cannot always satisfy optimality necessary conditions. In order to overcome the above drawbacks, an improved direct collocation method is proposed by Dosthosseini et al. [107] to find optimal solution of HEVs control problem. This improved direct collocation method is based on orthogonal polynomials, also called as pseudo-spectrum method. The main advantage of this pseudo-spectrum method is that it can improve the accuracy of approximate optimal solution by relatively few discrete points. Meanwhile, the optimality of the solution can also be guaranteed.

4.2.1.1.3. Other methods. Other optimization methods that have been used in energy management optimization control for HEVs include GT [108], stochastic optimal control [109] and nonlinear optimal regulation feedback control [110]. Although GT is a mathematic approach to understand human behaviors which is initially developed in economics, it has also been applied to design energy management strategies of HEVs. GT decouples optimal solution from driving cycle, and offline computation of GT is simpler than SDP. However, the robustness of GT is rather weak. Stochastic optimal control can maximize expected time of HEVs to operate without constraint violation, but online estimation of transition probabilities and online reconfiguration of the control law are usually difficult. Nonlinear optimal regulation feedback control can ensure optimality and stability, but it is sensitive to calibration parameter.

4.2.1.2. Static optimization method. The solving methods for static optimization problem can be roughly divided into gradient-based methods and derivative-free methods. Gradient-based methods use derivative information of objective function to solve such optimization problem. For example, sequential quadratic programming (SQP) algorithm has been applied in the optimization of energy management strategy parameters for a parallel HEV [111]. The main drawback of gradient-based methods is that they cannot find global optimum since being trapped in local minimum. Furthermore, strong assumptions of objective function are required to obtain the derivative, such as continuity, differentiability, satisfying the Lipschitz condition and so on. Due to noisy, discontinuous and multi-modal nature of HEV optimization problems, gradient-based methods are not suitable for control strategy optimization of HEVs.

Derivative-free methods find optimal solution by iterative method rather than relying on the derivatives, which have been proved to be appropriate for energy management strategy optimization of HEVs. Moreover, such approaches are superior to gradient-based methods in searching global optimum over entire design space. Derivative-free methods that applied to energy management strategy optimization of HEVs mainly include simplex method [112], modified simplex method [113], complex method [114], DIRECT [115] and stochastic search methods (also called meta-heuristic search methods) [116–121]. A summary of gradient-based methods and derivative-based methods is given in Table 1. Due to global optimality and robustness, stochastic search methods are more suitable to optimization control problems of HEVs and thus attract more attention. These stochastic search methods include GA [116], SA [117], PSO [118], EA [119], BA [120], and PCOA [121]. Each algorithm has its own advantages and disadvantages, as shown in Table 2. Adaptive SA (ASA) [122], adaptive differential evolution algorithm (ADEA) [123], genetic-algorithm swarm hybrid algorithm [124], real-valued GA (RGA) [125], space exploration and unimodal region elimination (SEUMRE) [126] also have been proposed to improve convergence speed and robustness.

Furthermore, based on derivative-free methods, multi-objective optimization problem is generally converted into single objective optimization problem by assigning weights to every objective function or considering only one objective as main objective and the others as constraints. However, optimal weights are very difficult to acquire; moreover, only one solution is acquired after the optimization. In order to overcome the above limits, varying-domain method is presented to give a flexible priority among multi-objectives [127], improved non-dominated sorting genetic algorithm (NSGA-II) is utilized to solve multi-objective problems directly [128].

However, like dynamic optimization methods, all above static optimization methods are sensitive to driving cycle. Hence, driving cycle recognition is also necessary for improving the adaptability of this kind of method [129].

4.2.2. *Real-time optimization energy management strategy*

The global optimization techniques are not directly applicable for real-time control system. By definition of an instantaneous cost function, a real-time optimization energy management strategy can be acquired. In order to guarantee electrical self-sustainability,

Table 1
A summary of gradient-based methods and derivative-free methods.

Algorithm type	Algorithm name	Advantages	Disadvantages
Gradient-based	SQP	Easy to implement; Effective for solving continuous and smoothing problems.	Requires imposing strong assumptions on objective function to obtain derivative; Only obtain local optimum.
Derivative-free	Simplex method	Easy to implement; Requires only function value without analytic expression and derivative; Has strong capability of local search.	Rely on a good initial point; Easy to get trapped in local optimum; Not suitable for high-dimensional, multiple-constraints problems and constrained optimization problems.
	Complex method	Easy to implement; Requires only function value without analytic expression and derivative.	Rely on a good initial point; Easy to get trapped in local optimum; Not suitable for high-dimensional, multiple-constraints problems.
	DIRECT	Requires no derivative of objective function; Not need to specify the starting point; Covers entire design space in search of global optimum; Does not have tuning parameters.	Slow convergence to true global optimum when reaching global optimal region; Does not have a convergence rule to determine the convergence of the optimization.
	Stochastic search methods	Requires no derivative of objective function; Can find global optimum; Has strong robustness and extensive application scope; Parallel calculation is possible; Easy to combine with other methods.	The performance depends on tuning parameters or initial random population; Slow convergence to true global optimum when reaching global optimal region.

Table 2
A summary of stochastic search methods.

Algorithm name	Advantages	Disadvantages
GA	Can find global optimum over entire design space; Has strong capability of global search; Has a strong universality.	The performance depends on initial random population and tuning parameters; Has weak capability of local search.
SA	Can find global optimum without covering entire design space; Has strong capability of local search.	The performance depends on tuning parameters; Has weak capability of global search.
PSO	Fewer parameters must be adjusted compared to SA and GA; Simple to understand and implement without natural operators compared to GA; Has stronger capability of local search compared to GA; Convergence speed is faster than GA.	Easy to get trapped in local optimum; The performance relies on the selection of the constants in the updating velocity and initial random population; Has weaker capability of global search compared to GA.
EA	Has good convergence properties compared to GA; Easy to understand; Fewer parameters must be adjusted compared to GA; Convergence speed is faster than GA.	The performance depends on tuning parameters.
BA	Has a higher convergence rate than GA.	The performance depends on tuning parameters; Easy to get trapped in local optimum.
PCOA	Has strong capability of global search.	Accuracy of optimal solution is relatively low.

instantaneous cost function should consider the variations of electrical energy as equivalent fuel consumption. Real-time optimization energy management strategy must be simple enough in order to be implementable with limited computation cost and memory resources. Moreover, manual tuning of control parameters should be avoided. In principle, the realization of a real-time optimization energy management strategy can be accomplished in several ways. So far real-time optimization energy management strategies that have been applied in energy optimal control of HEVs are shown in Fig. 5. All these types of real-time optimization energy management strategies will be discussed in detail in the next section.

4.2.2.1. ECMS. ECMS is one of the well-known real-time optimization energy management strategies, which has been originated by Paganelli et al. [130]. The main idea of ECMS is to reformulate global optimization problem into local optimization problem by minimizing equivalent fuel consumption that is the sum of actual fuel consumption from ICE and converted fuel consumption from ESS. Based on PMP, an equivalence factor is proposed to convert electric energy to equivalent fuel energy, equivalent to the costate of PMP. As an approximate realization of PMP [131], ECMS can be applied as a real-time optimization energy management strategy. However, control performance of HEVs is heavily dependent on proper estimation of equivalence factor. Optimal equivalence factor is related to driving cycle, battery SOC limits and the direction of electric current that are generally unpredictable. Therefore, equivalence factor is the key of ECMS, which has been studied extensively by a large number of scholars. The study of equivalence factor mainly involves estimation methods as well as impact factors.

In general, these estimation methods can be classified into two kinds. The first kind of estimation methods is to assume that equivalence factor is constant during driving cycle. Optimal constant equivalence factor can be obtained based on average energy conversion efficiency between fuel and electrical energy [132], shooting algorithm [133], offline global optimization such as DP [134], DP-based marginal cost method [135], GA [136], and ant colony optimization algorithm [137]. Although such methods are very simple, full knowledge of driving cycle must be known in advance, re-calibration of equivalence factor is a necessity for individual driving cycle, thus limiting the generality of ECMS. The second kind of estimation methods is to calculate variable equivalence factor online, which can be further divided into three sub-categories.

The first category considers battery SOC limits during driving cycle. Due to similarity between equivalence factor and the costate, based on the first estimation method of the costate, equivalence factor function can be composed of constant optimal equivalence factor obtained from offline optimization combined with a SOC or SOE correction term that is formulated as a P control [138], or a PI control [139], or other nonlinear feedback control [135]. Moreover, it also can be computed based on battery SOC error that is designed as a PI control [140], or based on battery SOC and speed constraint [141]. The main drawback of such approaches is that the equivalence factor function is sensitive to driving cycle. Pei et al. [135] overcome this weakness by adding an adaptive law to above equivalence factor function. Furthermore, adding battery SOC deviation into cost function can meet the requirement of battery SOC limits, but will make a certain sacrifice of fuel economy due to unexpected behaviors of the battery. So, a new SOC-sustaining strategy is presented to further improve optimization performance by eliminating SOC deviation from cost function and determining search space of optimization parameters based on upper and lower SOC limits [142].

The second category considers both battery SOC limits and the direction of electrical current to improve the robustness of the first kind of approach to driving cycle variations. A two-argument function based on SOC and the derivative of SOC is defined to calculate equivalence factor in [143], while equivalence factor function consists of the pair of optimal equivalence factor (S_{chg}, S_{dis}) and a probability factor based on current electrical energy usage and future energy usage in [144].

The third category considers battery SOC limits and driving cycle information, which is similar to the second estimation approach of the costate. According to the level of preview information, different maps of equivalence factor and relevant factors are constructed to update equivalence factor. Equivalence factor can be related to (1) battery SOC and vehicle position [145–146], (2) battery SOC, vehicle position, elevation profile and average speed [147], (3) battery SOC, trip length and elevation change [148], and (4) battery SOC, past and predicted vehicle speed and GPS data [149]. Such approaches do not require full knowledge of driving cycle, thus can be applied in real-time control system by employing past, current and future information from in-vehicle 3D maps [145], GPS-based navigation system [147–149], and telemetry system [146]. ECMS based on such estimation method is also called as A-ECMS or telemetric ECMS (T-ECMS). The weakness of this type of approach is that prediction methods of driving cycle information generally suffer from prediction error and huge computational cost. Considering above shortcoming, on one hand, driving cycle recognition algorithm is used to update equivalence factor [150]; on the other hand, the influence of optimization window sizes and prediction error [151], driving profiles [152], the level of preview information [148] on equivalence factor and control performance of ECMS are analyzed in detail to identify the most effective prediction method of preview information for real-time calculation of equivalence factor.

4.2.2.2. MPC. MPC is a popular strategy that has been widely employed in industry to deal with multivariable constrained control problems. MPC generally consists of three main steps: (1) calculate optimal control sequence in a prediction horizon that minimizes cost function subject to constraints; (2) implement the first part of derived optimal control sequence to physical plant; and (3) move entire prediction horizon one step forward and repeat step 1 [153].

As described above, unlike DP or PMP, MPC is an optimization-based receding horizon control strategy, which has the potential to reduce computational effort and be implemented in HEVs. However, the solution method of DP or PMP still can be used to find optimal solution at each time step in the MPC framework. That is why MPC's solution will be suboptimal. Due to its receding horizon nature, MPC can adapt to the variations of driving cycles. Since the optimization problem is solved over a future prediction horizon in MPC, MPC is neither short-sighted nor sensitive, which is an advantage over ECMS. However, future driving cycle must be known in advance by the method of prediction or recognition.

Based on the characteristics of control-oriented model, MPC can be classified into linear varying-time MPC (LTV-MPC) and nonlinear MPC. Although linearization of nonlinear plant model and constraints can reduce computational complexity, model error introduced by linearization becomes an obstacle to hinder HEVs from improving fuel economy further [154]. Nonlinear MPC can noticeably improve fuel economy, but computational cost is higher than that of LTV-MPC [155–156]. On the basis of the capability of responding to drivers' actions, MPC can also be divided into classical MPC and stochastic MPC (SMPC). SMPC can improve closed-loop control performance of classical MPC by introducing a stochastic driver model [157]. Compared to SDP, SMPC can easily adapt itself to the change of stochastic parameters and it can also be applied to high order models. SMPC with learning (SMPCL) is proposed to improve adaptation of SMPC to environmental changes and proved to have good performance close to MPC with full knowledge of future driving information [158].

According to prediction methods for future torque demand, MPC can be grouped into two subcategories: (1) MPC based on navigation technology or vehicle-mounted sensors and (2) MPC based on mathematical prediction model. In MPC based on navigation technology or vehicle-mounted sensors, road information in future horizon can be acquired by vehicle-mounted sensors [155] or GPS [159] or ITS [160]. Optimization performance of this kind of MPC heavily relies on the accuracy of information from vehicle-mounted sensors, GPS and so on. However, the stability of GPS system cannot be guaranteed in real-time control system of HEVs, meanwhile, update time of GPS information cannot meet the requirement of real-time control for HEVs. Moreover, the cost of vehicle-mounted sensors is too high. Due to the weakness of MPC based on navigation technology or vehicle-mounted sensors above mentioned, obtaining prediction information by mathematical model has drawn much attention of relevant scholars, thus formulating MPC based on mathematical prediction model. In this kind of MPC, mathematical prediction models consist of two types: one provides deterministic torque demand over prediction horizon, for example, future torque demand can be assumed to be exponentially decreasing in the prediction horizon [161], the other describes probability distributions of future torque demand based on current driving cycle or historical data, e.g., various standard driving cycles are used to acquire probability distributions of future torque demand in [162].

4.2.2.3. ES. ES is a non-model-based adaptive control algorithm, which can dynamically search optimum point of performance function of a system. Therefore, ES is very suitable to real-time optimization of nonlinear, dynamical systems, e.g., HEVs. ES is first applied to power split control of HEVs by Dincmen et al. [163] in 2010. Compared to ECMS, proposed ES-based energy management strategy no longer needs to calculate equivalence factor, but it also only obtains local optimal solution. In order to realize a better local optimization, Wang et al. [164] propose a SDP-ES energy management strategy for HEVs, which combines the advantages of both SDP and ES. In SDP-ES energy management strategy, SDP is used to ensure global optimality and SOC sustainability of ESS while ES is employed to search local optimum online. Although ES-based energy management strategy has the potential to be implemented in real-time control system, the study on ES-based energy management strategy of HEVs still remains in the simulation phase with single objective.

4.2.2.4. Robust control. Robust control is a kind of output feedback control whose parameters are tuned such a way that matrix norms or signal norms of close loop systems are in desired boundaries. Above norms are defined according to design requirements like robustness or disturbance rejection. So, robust control is very suitable to nonlinear, time-varying systems. Moreover, robust control is derived based on dynamic models, thus it can be used in real-time optimization control of HEVs. Pisu et al. [165], Reyss et al. [166], Fekri et al. [167] apply robust control using mixed-μ synthesis to torque management of HEVs, guaranteeing the stability and performance robustness subject to parametric uncertainties, unmodeled complex-valued uncertainty, sensor noises and estimation errors. However, robust control can only obtain sub-optimal solution like other real-time optimization energy management strategies. Besides, robust control requires much effort in the manipulation of system equations. Mathematical complexity as well as simplification of a nonlinear time-varying system to a linear time-invariant system has prevented further development of robust control in the field of energy management for HEVs.

4.2.2.5. Intelligent control strategy. Intelligent control takes reasoning decisions by emulating human brain, according to quantitative and qualitative information of controlled system, which is well suited to the control of complex nonlinear system. This characteristic has facilitated widespread use of intelligent control strategies in the control of HEVs. Among intelligent control strategies, machine learning algorithms are mostly used in energy management control of HEVs, including NN [168], Elman neural network (ENN) [169], SVM [170], recursive least square (RLS) [171] and other machine learning algorithms [172]. For machine learning algorithms, precise powertrain models are no longer needed while computational effort is reduced extremely. Nevertheless, on one hand, creating required full and correct database is difficult and time consuming, especially for optimized train database such as DP [173]; on the other hand, structure sizes of the database directly affects computation time and the performance of controlled system. Although fuzzy c-means clustering algorithm and an agent-based architecture have been proposed to overcome above drawbacks [174], this kind of approach can also only obtain suboptimal solution.

4.2.3. Characteristics of optimization-based energy management strategy

Optimization-based energy management strategy minimizes cost function which is numerical description of HEVs' system performance requirements through different optimization control approaches. Different cost functions forms various types of optimization control problems, thus different optimization-based energy management strategies have been proposed to solve above optimization control problems including global optimization energy management strategy and real-time optimization energy management strategy.

When formulated in dynamic optimization problems, dynamic optimization methods can obtain the optimum with huge computation cost. When formulated in static optimization problems, static optimization methods gain near optimum with smaller computation cost than dynamic optimization methods. When converting dynamic optimization problems into mathematical programming problems, although computational time can be reduced significantly, modeling errors introduced by model approximations of powertrains will sacrifice precise of the optimum. In general, due to preview nature and computational complexity, global optimization energy management strategy is not applicable to real-time control system of HEVs. However, it can be used as an evaluation, comparison and analysis tool of HEVs' energy management strategy. First, it can identify maximal potential performance of a given powertrain configuration for HEVs. Second, it can serve as a benchmark for evaluating the effectiveness of other energy management strategies. Finally, it can also be employed to derive implementable rules for rule-based energy management strategy. This is why global optimization energy management strategy has received most attention.

When formulated in instantaneous optimization problems, real-time optimization energy management strategy is applied. Real-time optimization energy management strategy must be simple enough in order to be implementable with limited computation cost and memory resources. Moreover, manual tuning of control parameters should be avoided. ECMS and MPC are the two most widely studied real-time optimization energy management strategies, which are respectively considered as the realization of PMP and DP. ECMS is sensitive to equivalence factor affected by driving cycle while MPC needs future driving information. Therefore, driving cycle information is also important for real-time optimization energy management strategy.

Although much effort has been made to improve the performance of optimization-based energy management strategy, a good balance between the optimality and implementation is difficult to realize. An easy, practical and optimization-based energy management strategy has not been offered so far.

4.3. Comparison and summary

On the basis of thorough analysis, it is clearly seen that rule-based energy management strategy and optimization-based energy management strategy have their own characteristics and application, as shown in Table 3. Rule-based energy management strategy is sole strategy that has been commercially implemented due to easy implementation, but it cannot obtain optimum solution. Optimization-based energy management strategy overcomes inherent drawback of rule-based energy management strategy through optimization control approach, whereas it is hard to implement in real-time control system even with real-time optimization energy management strategy. In order to obtain practical and optimal energy management strategy of HEVs, related research focus on improving optimality of rule-based energy management strategy and reducing computation load of optimization-based energy management strategy. Though control principle of both types of energy management strategy is completely different, control performance of them is related to driving cycle. Therefore, driving cycle prediction and recognition algorithms are widely studied during the development of energy management strategy for HEVs, however, they usually increase computational time further.

5. Future trends of energy management strategy for HEVs

In light of quantitative and qualitative analysis of current situation for HEVs' energy management strategy, there are still some problems to be solved as well as room to improve control performance of energy management strategy for HEVs.

Firstly, control effects of all existing energy management strategies are affected by driving cycle. Therefore, intelligent energy management strategy including driving cycle recognition or driving cycle prediction is a promising solution to improve the performance of HEVs. However, driving cycle recognition or prediction algorithm generally will increase computation load, and prediction information provided by vehicle-mounted sensors or navigation system may include uncertainties and disturbances. A simple, practical, effective and robust recognition or prediction algorithm of driving cycle needs to be presented, which is a significant research direction of the research in the field of energy management strategy of HEVs.

Secondly, integrated, multi-objective and coordinated optimization energy management strategies, which combine energy conservation (fuel economy), environmental protection (emissions), safety (fault tolerance and component durability), and comfort (drivability), are necessities for commercially high-performance HEVs, which are also ultimate objectives of energy management control of HEVs. Most of available energy management strategies only consider fuel economy of HEV, even if a small amount of energy management strategies take into account other performance indices such as emission and drivability, these performance indices almost are expressed as penalty term in the optimization problems. However, for HEVs, environmental protection, safety and comfort are as important as energy conservation. Although convex optimization has been considered as an efficient energy management strategy for dimensioning of powertrains, energy management control, engine on/off control and gear shifting control of HEVs simultaneously [175], approximation methods of powertrains as well as influence of modeling errors on control performance should be carefully studied. Moreover, other feasible energy management strategies should also be explored.

Thirdly, the tradeoff between computation complexity and optimization performance of energy management strategy remains an open issue. The existing approaches all reduce computation load at the expense of optimization performance. These are only considered as interim solutions not final solutions. Cloud computing may be a good solution to handle complexity computation as well as to keep the optimality of energy management strategy. In addition, before new feasible real-time optimization algorithms appear, the way of reducing calculation amount of existing optimization algorithms without sacrificing significant performance through appropriate simplification is another solution. The simplification may be aimed at optimization problems or implementation ways of optimization algorithms or powertrain models or above three, which needs extensive study.

Finally, every energy management strategy has its own merits and demerits. A fair and credible evaluation system of energy management strategies is helpful to design a suitable energy management strategy for specific HEV with particular performance objectives. Also, it is meaningful to establish corresponding evaluation system for filling above gaps.

6. Conclusions

Based on bibiometrics, this paper thoroughly analyzes development status of energy management strategies for HEVs through content analysis involving author keywords and abstracts, thus gives a comprehensive quantitative description for the first time. Based on quantitative analysis, qualitative analysis of whole existing energy management strategies for HEVs are presented and discussed.

Table 3
Characteristics of various types of energy management strategies.

Strategy type	Advantages	Disadvantages	Applications
Deterministic rule-based energy management strategy	Computationally efficient; Easy to implement.	Requires extensive calibration and tuning of the parameters; Cannot guarantee the optimality; Non-portability.	Widely used in HEV prototypes and commercial HEVs.
Fuzzy rule-based energy management strategy	Has the robustness to measurement noise and component variability; Low computation; Easy to implement.	Cannot guarantee the optimality; Requires calibrating membership function and fuzzy rule; Non-portability.	Used in HEV prototypes and commercial HEVs.
Real-time optimization energy management strategy	Has the potential to be implemented on HEVs; Can obtain sub-optimal solution.	Cannot obtain global optimal solution; Still difficult to be implemented in current vehicle controller.	Used in HEV prototypes.
Global optimization energy management strategy	Can obtain optimal solution; Requires no calibration.	Requires a-priori knowledge of driving cycle; Computation is the most complex; Cannot be implemented directly.	Identify maximal potential performance of specific HEV; Evaluating the effectiveness of other energy management strategies; Derive implementable rules for rule-based energy management strategies.

Classification and comparison of different energy management strategies are based on the control theory. The pros and cons of each energy management strategy are summarized in detail. The optimality and implementation are two main concerns in designing energy management strategies, but there is a tradeoff between them. Driving cycle is common influence factor of all energy management strategies. Future trends of energy management strategies are derived from comprehensive analysis combining quantitative and qualitative analysis to improve control performance of HEVs. Proposing simple, practical, effective and robust driving cycle recognition/prediction algorithms, developing integrated multi-objective, coordinated optimization energy management strategies, realizing a good balance between computation complexity and optimization performance of energy management strategies, establishing a fair and credible evaluation system of energy management strategies are four development trends. The original work of this paper not only provides a broader vision for relevant researchers but also facilitate the design of simple, practical, optimal energy management strategy.

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