Implementing an Adaptive Algorithm for Hybrid EVs: Recognising Driving Patterns with Artificial Intelligence

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Abstract. This review article delves into the enhancement of fuel efficiency in hybrid electric vehicles (HEVs) through the use of adaptive algorithms for precise driving pattern recognition. The review explores studies that delve into two distinct methodologies. Firstly, a method utilising a Learning Vector Quantisation neural network is highlighted, which analyses six standard driving cycles. By employing micro-trip extraction and Principal Component Analysis, this method ensures a comprehensive training sample, subsequently simplifying the model and reducing data convergence time. Simulations reveal a significant reduction in sampling duration whilst maintaining satisfactory accuracy, leading to an 8% improvement in fuel economy when paired with a parallel hybrid vehicle model. Additionally, the article examines the Neural Network Fuzzy Energy Management Strategy (NNF-EMS), designed to address the adaptability constraints of traditional energy management strategies. Through neural network learning and parameter analysis, the NNF-EMS showcases enhanced adaptability and practicality across diverse driving cycles, underscoring the potential of artificial intelligence in HEV algorithm development..

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1 Introduction

The growing interest in hybrid electric vehicles (HEVs) is largely due to their potential to improve fuel efficiency and reduce harmful emissions. A key factor in enhancing the performance of HEVs is the control strategy used in their powertrains. Various control strategies have been developed to improve the operational efficiency of HEVs, and among them, the flexibility of these strategies is found to be crucial. This review aims to delve into the identification of vehicle driving patterns to enhance this flexibility, which in turn, is expected to improve the fuel economy of HEVs, a theme echoed in the studies under review.

Driving Pattern Recognition (DPR) has been identified as a significant aspect of creating a more adaptive control strategy for HEVs. It provides crucial driving information to the vehicle's main controller, allowing for better adaptability to different driving conditions. There are two main methods to identify vehicle driving patterns: one is based on using external traffic environment information, and the other relies on analysing driving information collected directly from the vehicle. This review focuses on the latter method, as it is based on the theoretical study of control algorithms, making it more straightforward to apply, a methodology explored in the studies under review.

A notable approach in this domain is the Intelligent Energy Management Agent (IEMA) proposed for parallel hybrid vehicles, which uses a Learning Vector Quantization (LVQ) network to identify different types of roadways. This mechanism has been found to be effective in classifying drive cycle segments. Moreover, the use of certain mathematical measures in DPR, particularly the Euclidean distance, has been identified as more adaptable. These findings form the basis upon which this review introduces new mathematical methods to enhance the performance of the LVQ network, as explored in the studies under review.

The selection of representative features is crucial for the effectiveness of DPR. Over time, there has been a move towards reducing the number of features selected for DPR, indicating a move towards more streamlined feature sets. The application of certain methods to increase the training sample quantity and reduce the input vector dimension has been explored in the studies under review. This approach optimises the pattern recognition model, leading to improved recognition accuracy with less computing effort and time. The control logic of HEVs, based on LVQ driving pattern recognition, optimises control parameters of specific driving cycles, showcasing a practical approach towards adaptive control in HEVs.

In conclusion, the exploration of innovative control strategies like the Neural Network Fuzzy Energy Management Strategy (NNF-EMS) based on Driving Cycle Recognition (DCR) presents a promising avenue for improving the adaptability of energy management systems in HEVs. By employing certain learning and analysis methods for the recognition of driving cycles, the NNF-EMS offers a robust and practical solution under varying driving cycles. This novel approach underscores the potential of integrating intelligent algorithm optimisation with existing control strategies to enhance fuel economy and reduce emissions in HEVs, thereby contributing to the broader goal of environmentally sustainable vehicular technologies.

2 Review and discussion

The Driving Pattern Recognition (DPR) model based on Learning Vector Quantisation (LVQ) Neural Network is a method devised to identify and categorise different driving patterns using a specific type of artificial intelligence network known as LVQ. Here's a breakdown of what this entails:

1. **Driving Pattern Recognition (DPR):**
   - This is about understanding and categorising the way a vehicle is being driven. For instance, recognising whether the driving pattern is aggressive, cautious, or economical. This recognition can be based on various factors like speed, acceleration, braking, and so on.
2. **Learning Vector Quantisation (LVQ) Neural Network:**
   - LVQ is a type of artificial neural network that is particularly good at categorising data. It learns from training data to categorise input data into predefined classes.

Now, when these two are combined:

- The DPR model utilises the LVQ Neural Network to learn from a set of training data where different driving patterns have already been identified and categorised.
- Once trained, the LVQ network can then analyse new driving data to identify and categorise the driving pattern. It does this by comparing the new data to what it has learned from the training data, and then categorising the driving pattern accordingly.
- The LVQ network adjusts itself through a process of self-organisation to accurately reflect the distribution of driving patterns based on the training data it received. This way, it gets better over time at recognising and categorising driving patterns.

In essence, this model is about employing a smart, learning-based network to understand and categorise how a vehicle is being driven, which can be crucial for various applications like improving fuel efficiency, enhancing safety, or customising the driving experience.

In a study by He et al. (2012), the focus was primarily on the development and verification of a Driving Pattern Recognition (DPR) model based on Learning Vector Quantization (LVQ) Neural Network [1]. The study meticulously outlines the structure and functionality of the LVQ network, the establishment of a driving pattern identifier model, and the process of training and verifying this model. The ultimate goal was to enhance the fuel economy of Hybrid Electric Vehicles (HEVs) by optimizing the control strategy through a better understanding of driving patterns. The following table encapsulates the key findings and methodologies employed in the study:

Table 1. LVQ Neural Network-Based Driving Pattern Recognition [3-9]

Section	Description	Methodology	Key Findings	Implications
LVQ Neural Network	Explanation of LVQ network's ability to adjust weights through self-organization to reflect data pattern distribution	Utilization of Kohonen competitive algorithm	Evolution from Kohonen competitive algorithm, wide application in pattern recognition	Basis for pattern recognition in DPR

Model Structure		Establishment of a driving pattern identifier model using Matlab/Simulink	Classification of input vectors into target patterns using Euclidean distances	Rapid classification through Euclidean distances	Enhanced accuracy in pattern recognition
Sample Training		Training process using principal components from standard driving cycles and micro-trips	Supervised training with continuous adjustment of competition layer weights	Continuous adjustment of competition layer weights	Optimization of training process
Identifier Model Verification		Verification of the model using a composite testing driving cycle	Comparison of pattern identification results of different types of driving cycles	Preliminary validation of model, identification of areas for optimization	Validation and identification of optimization areas
Simulation Experiment	DPR Application	Co-simulation of LVQ neural network identifier with a parallel HEV model	Comparison of engine and motor torque results with and without DPR optimization	Improved fuel economy by up to 8.51%, less fluctuation in engine output torque with DPR optimization	Demonstrated fuel economy improvement
	Fuel Consumption Comparison	Illustration of fuel consumption reduction through DPR optimization	Optimization of control parameters based on DPR result	Fuel consumption reduced by 8.51% compared to non-optimized case	Significant fuel economy improvement

The authors implemented a Driving Pattern Recognition (DPR) model using a Learning Vector Quantisation (LVQ) Neural Network to improve the fuel economy of Hybrid Electric Vehicles (HEVs). Here are some key methodologies and technical details elucidated from the text:

- **LVQ Neural Network Architecture:**
    - The Learning Vector Quantisation (LVQ) Neural Network is a clever mechanism that adjusts itself by organising its internal weights when fed with a plethora of training samples. It's a descendant of the Kohonen competitive algorithm and has carved a niche for itself in the realm of pattern recognition. Essentially, it's like a smart system that learns to recognise patterns by adjusting its internal settings, much like tuning a radio to catch a station clearly.
- **Driving Pattern Identifier Model:**

  - The authors crafted a model using Matlab/Simulink to identify driving patterns. This model leans on the LVQ neural network to sort input vectors into specific target patterns, which in layman's terms, means identifying different driving behaviours. It's akin to having a smart assistant in your car that understands your driving habits and adjusts the car's settings to match them.
- **Euclidean Distance Calculation:**
  - The model employs a mathematical method called Euclidean distance calculation to swiftly classify input vectors into subclasses. It's a bit like measuring the similarity between your current driving pattern and stored patterns to quickly identify which category your driving fits into.
- **Sample Training:**
  - The authors fed the system with a rich diet of training data derived from various driving cycles and micro-trips. This supervised training helped in fine-tuning the system's ability to recognise driving patterns. It's akin to teaching a dog new tricks; the more you train it, the better it gets.
- **Identifier Model Verification:**
  - To ensure their model was up to snuff, the authors tested it using a composite testing driving cycle. This step was crucial to ascertain the model's accuracy and stability in identifying different driving patterns across varied cycles.
- **Simulation Experiment:**
  - They conducted a simulated experiment coupling the LVQ neural network identifier with a parallel HEV model to gauge the impact on fuel economy. The comparison of engine and motor torque with and without Driving Pattern Recognition (DPR) optimisation shed light on the benefits of DPR in reducing engine output torque fluctuations and enhancing fuel economy.
- **Optimisation Techniques:**
  - Employing techniques like micro-trip extraction and Principal Component Analysis (PCA), the authors fine-tuned the training of the LVQ identifier. This helped in reducing the computational load while maintaining a high level of identification accuracy.
- **Real-Time Control Strategy Adjustment:**
  - The authors proposed a real-time adjustment of control strategies based on the results from the DPR. This innovative approach aims for a near-global optimised control strategy, making the HEV more adaptable to varying driving patterns, which in turn, could lead to better fuel economy.

These methodologies, articulated in a structured and systematic manner, underscore the potential of integrating intelligent systems in HEVs to recognise driving patterns, which could be a linchpin in enhancing fuel economy and overall vehicle efficiency.

The overall study by He et al. (2012)provides a robust framework for understanding how the integration of LVQ Neural Network in DPR can significantly enhance the adaptability of control strategies in HEVs. The methodologies employed in the study, particularly the creation and verification of a driving pattern identifier model, offer a substantial foundation upon which the discussion on implementing adaptive algorithms can be based. The simulation experiments conducted in the study, showcasing an improvement in fuel economy, align seamlessly with the overarching theme of our review article, which is to explore the potential of artificial intelligence in recognising driving patterns to optimise the operational efficiency of HEVs. The nuanced understanding of driving patterns, as elucidated in the study, presents a compelling case for the integration of artificial intelligence in the energy management systems of HEVs, thereby making a significant stride towards achieving better fuel economy and reduced emissions.

Another study by Zhang et al. (2020) delves into the intricacies of Fuzzy Energy Management Strategy (F-EMS) for Hybrid Electric Vehicles (HEVs) [2]. The study explores the potential of fuzzy control in managing the energy distribution in HEVs, contrasting it with deterministic control strategies. Here are the summarised key findings from the study [10-15]:

- **Fuzzy Energy Management Strategy (F-EMS) for Hybrid Electric Vehicles (HEVs):**
  - **Fuzzy Control:** Fuzzy control uses vague or "fuzzy" rules based on experience and reasoning, as opposed to traditional control strategies that use precise mathematical rules. This approach is more adaptable to uncertainties, making it suitable for managing complex systems like HEVs.
  - **Control Rules:** Fuzzy control rules are expressed in a human-like language, which makes them easy to understand and implement. These rules help in managing the energy in HEVs efficiently, especially in varying driving conditions.
  - The study found that the F-EMS could effectively manage the energy distribution between the engine and the battery, ensuring optimal performance and fuel economy.
- **Fuzzy Logic Models:**
  - **Mamdani Model:** This is a type of fuzzy logic model used for energy management in HEVs. It helps in determining how the battery and engine should operate under different conditions to ensure efficient energy use.
  - The authors utilized the Mamdani model to develop the fuzzy rule base and membership functions for the F-EMS.
- **Fuzzy Control Rules for HEVs:**
  - **Rule Base:** The set of fuzzy rules that guide how the HEV should operate under different conditions.
  - **Input Fuzzification:** Converting precise inputs like battery charge level and demanded torque into fuzzy values that can be used in the fuzzy rules.
  - **Fuzzy Reasoning:** Using the fuzzy rules and fuzzy inputs to determine how the battery and engine should operate.
  - **Clear Output:** Converting the fuzzy decisions into precise actions for the battery and engine.
  - The authors developed a set of fuzzy control rules that were effective in managing the energy distribution in HEVs, particularly under varying driving conditions.
- **Neural Network Fuzzy EMS (NNF-EMS) Based on Driving Cycle Recognition (DCR):**
  - **Combining Neural Networks and Fuzzy Logic:** This approach combines the learning ability of neural networks with the adaptable reasoning of fuzzy logic to better manage energy in HEVs under varying driving conditions.

    - **Driving Cycle Recognition (DCR):** Identifying the driving conditions (e.g., city driving, highway driving) and adjusting the energy management strategy accordingly to improve fuel economy and reduce emissions.
    - The NNF-EMS, which integrated neural networks for driving cycle recognition, showed improved performance in managing energy distribution, leading to better fuel economy and reduced emissions.
- **Simulation and Analysis:**
    - **Simulation Models:** The study used simulation models to test the performance of the proposed NNF-EMS under different driving cycles (e.g., NEDC and FTP75).
    - **Performance Metrics:** The performance of the NNF-EMS was evaluated based on fuel economy, emissions, and vehicle velocity performance.
    - **Comparison with Traditional F-EMS:** The NNF-EMS showed better performance in terms of fuel economy and emissions compared to traditional F-EMS, especially under real transient driving conditions.
    - Through simulation, the authors demonstrated that the NNF-EMS outperformed the traditional F-EMS in terms of fuel economy and emissions, especially under real transient driving conditions.
- **Results of the study:**
    - **Adaptive Optimization:** The proposed NNF-EMS can adaptively optimize the fuzzy rules and membership functions under different driving cycles, showing better performance than traditional fuzzy control strategies.
    - **Practical Implications:** The study suggests that the proposed method could have practical value in improving the fuel economy of hybrid electric vehicles, especially as vehicles evolve towards being more connected and potentially autonomous.
    - **Results:** The authors concluded that the NNF-EMS has the potential to significantly improve the fuel economy of HEVs and suggested that future research could explore its application in more connected and potentially autonomous vehicles.

This summary encapsulates the core insights from the study by Zhang et al. (2020), shedding light on the potential of fuzzy control strategies in enhancing energy management systems of hybrid electric vehicles, and the promising direction of integrating real-time driving condition recognition to further optimise energy efficiency and emission performance.

The study by Zhang et al. (2020) delves into the potential of employing Artificial Intelligence (AI) to enhance the efficiency of Hybrid Electric Vehicles (HEVs) through adaptive algorithms. By utilising fuzzy logic and neural networks, the research illustrates a methodology to tackle the uncertainties inherent in varying driving conditions. The crux of the study revolves around Driving Cycle Recognition (DCR), which is about discerning different driving scenarios such as city or highway driving, and tweaking the energy management strategy accordingly. This AI-driven recognition allows the energy management system to make well-informed decisions on energy distribution between the engine and the battery, aiming for optimal fuel economy and reduced emissions.
The findings from the study are quite promising, showcasing through simulation that recognising driving patterns and adapting the energy management strategy can indeed lead to better fuel economy and reduced emissions. This not only underscores the practical value

of implementing such adaptive algorithms in real-world HEVs but also hints at a future where vehicles, especially hybrid and electric ones, could become smarter and more efficient by leveraging AI. As the automotive landscape evolves towards more connected and potentially autonomous vehicles, having an adaptive algorithm that can optimise energy management based on recognised driving patterns could be invaluable, marking a significant stride towards the future of intelligent and efficient vehicle systems.

3 Future Scope of Research

The integration of Artificial Intelligence (AI) in Hybrid Electric Vehicles (HEVs) offers a promising avenue to significantly enhance vehicular efficiency and reduce emissions. The potential of adaptive algorithms in recognising driving patterns and optimising energy management has been highlighted, but there's still a vast expanse of uncharted territory in this domain. The following pointers suggest potential directions for future research:

- **Advanced Driving Cycle Recognition (DCR):**
  - Enhance the accuracy and real-time responsiveness of DCR systems to cater to a broader spectrum of driving scenarios.
  - Investigate the potential of integrating real-time traffic data and weather conditions into DCR systems to refine energy management strategies further.
- **Holistic Energy Management Systems:**
  - Develop comprehensive energy management systems that not only optimise fuel efficiency but also enhance the overall driving experience.
  - Explore the synergy between adaptive algorithms and other vehicular systems such as Advanced Driver-Assistance Systems (ADAS) and Vehicle-to-Everything (V2X) communication.
- **Real-world Testing and Validation:**
  - Conduct extensive real-world testing to validate the efficacy and robustness of adaptive algorithms under diverse driving conditions.
  - Establish a framework for continuous learning and adaptation based on real-world driving data.
- **Standardisation and Policy Framework:**
  - Work towards the standardisation of adaptive algorithms to ensure interoperability and ease of integration across different vehicle models and brands.
  - Engage with policymakers to establish a conducive regulatory framework that fosters innovation while ensuring safety and compliance.

4 Knowledge Gaps

The endeavour to seamlessly integrate AI into HEVs has unveiled several knowledge gaps. These gaps underscore the need for further exploration and research. Recognising and addressing these gaps is crucial to guide future research and policy directions. Here are some of the predominant knowledge gaps in this domain:

- **Granular Understanding of Driving Behaviours:**
  - Delve deeper into the intricacies of various driving behaviours and their impact on energy consumption in HEVs.

- Explore the potential of personalised adaptive algorithms that can learn and adapt to individual driving styles over time.
- **Cross-vehicle Algorithm Transferability:**
  - Investigate the transferability of adaptive algorithms across different HEV models and configurations.
  - Understand the challenges and limitations associated with deploying a standardised adaptive algorithm across a diverse fleet of HEVs.
- **Long-term Efficacy of Adaptive Algorithms:**
  - Assess the long-term efficacy and reliability of adaptive algorithms in real-world scenarios.
  - Explore the maintenance and update requirements to ensure continuous optimisation of energy management strategies.
- **Cybersecurity and Data Privacy:**
  - Address the cybersecurity risks associated with the integration of AI and connectivity in HEVs.
  - Ensure robust data privacy and protection frameworks to safeguard sensitive information that may be collected and processed by these advanced vehicular systems.

5 Conclusion

The exploration into the realm of Artificial Intelligence (AI) for enhancing the efficiency and functionality of Hybrid Electric Vehicles (HEVs) has unearthed a plethora of insights. The meticulous review of the selected articles has not only fortified the understanding of the current landscape but also illuminated the path for future endeavours. Here are six key findings that subtly tie back to our review and provide a succinct recapitulation of our investigative journey:

- **Driving Cycle Recognition (DCR):**
  - The pivotal role of DCR in optimising energy management strategies in HEVs has been underscored. The ability to accurately recognise and adapt to varying driving patterns significantly contributes to fuel efficiency and emissions reduction.
- **Adaptive Algorithms:**
  - Adaptive algorithms emerge as a cornerstone for realising the full potential of HEVs. Their capability to learn and adjust to dynamic driving conditions is instrumental in bridging the gap between theoretical efficiency and real-world performance.
- **Real-world Validation:**
  - The emphasis on real-world testing and validation resonates through the reviewed literature. It's imperative to assess the robustness and efficacy of adaptive algorithms under diverse, real-world driving scenarios to ensure their reliability and effectiveness.
- **Holistic Energy Management:**
  - A holistic approach to energy management, encompassing not just fuel efficiency but also the overall driving experience, is advocated. This holistic perspective paves the way for a more integrated and user-centric approach to energy management in HEVs.
- **Standardisation and Policy Engagement:**

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    - The discourse around standardisation and policy engagement reflects the necessity for a conducive regulatory environment. It's crucial to foster a collaborative ecosystem that encourages innovation while ensuring safety, interoperability, and compliance.
- **Cybersecurity and Data Privacy:**
    - The integration of AI and connectivity in HEVs brings forth critical considerations around cybersecurity and data privacy. Ensuring robust protection frameworks is paramount to safeguard sensitive data and maintain the trust and confidence of users.

The synthesis of these findings resonates with the essence of our review, accentuating the transformative potential of AI in revolutionising the energy management paradigms of HEVs. The journey through the intricacies of adaptive algorithms and driving pattern recognition has not only enriched the understanding of the current state-of-the-art but also carved out the trajectory for future research endeavours in this exciting and impactful domain.

6 References

1. He, H., Sun, C., & Zhang, X. (2012). A method for identification of driving patterns in hybrid electric vehicles based on a LVQ neural network. Energies, 5(9), 3363-3380.
2. Zhang, Q., & Fu, X. (2020). A neural network fuzzy energy management strategy for hybrid electric vehicles based on driving cycle recognition. Applied Sciences, 10(2), 696.
3. Langari, R., & Won, J. S. (2003, May). Integrated drive cycle analysis for fuzzy logic based energy management in hybrid vehicles. In The 12th IEEE International Conference on Fuzzy Systems, 2003. FUZZ'03. (Vol. 1, pp. 290-295). IEEE.
4. He, H., Liu, Z., Zhu, L., & Liu, X. (2012). Dynamic coordinated shifting control of automated mechanical transmissions without a clutch in a plug-in hybrid electric vehicle. Energies, 5(8), 3094-3109.
5. Zhang, C., Vahidi, A., Pisu, P., Li, X., & Tennant, K. (2009). Role of terrain preview in energy management of hybrid electric vehicles. IEEE transactions on Vehicular Technology, 59(3), 1139-1147.
6. Lin, C. C., Jeon, S., Peng, H., & Moo Lee, J. (2004). Driving pattern recognition for control of hybrid electric trucks. Vehicle System Dynamics, 42(1-2), 41-58.
7. Won, J. S., &Langari, R. (2005). Intelligent energy management agent for a parallel hybrid vehicle-part II: torque distribution, charge sustenance strategies, and performance results. IEEE transactions on vehicular technology, 54(3), 935-953.
8. Feng, L., Liu, W., & Chen, B. (2012). Driving pattern recognition for adaptive hybrid vehicle control. SAE International Journal of Alternative Powertrains, 1(1), 169-179.
9. Jie, X., Hongwen, H., & Xiaowei, Z. (2010). Genetic-fuzzy HEV control strategy based on driving cycle recognition.
10. Zhou, M., Zhang, Y., Yang, Z., & Kang, D. (2011). Fuzzy energy management strategy for HEV based on particle swarm optimization with compressibility factor. Electr. Mach. Control, 15, 67-72.
11. Pei, J., Su, Y., & Zhang, D. (2017). Fuzzy energy management strategy for parallel HEV based on pigeon-inspired optimization algorithm. Science China Technological Sciences, 60, 425-433.

https://doi.org/10.1051/e3sconf/202454002020

12. Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]. IEEE Transactions on automatic control, 42(10), 1482-1484.
13. Li, H., Xu, D., & Wang, L. (2018, October). Application of fuzzy algorithms based on neural networks to the hybrid energy management systems of future combat vehicles. In 2018 International Conference on Sensor Networks and Signal Processing (SNSP) (pp. 475-481). IEEE.
14. Ericsson, E. (2000). Variability in urban driving patterns. Transportation Research Part D: Transport and Environment, 5(5), 337-354.
15. Ericsson, E. (2001). Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. Transportation Research Part D: Transport and Environment, 6(5), 325-345.