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PREDICTIVE ANALYSIS OF THE VARIOUS COMPONENTS ON A HYBRID ELECTRIC VEHICLE AT VARIABLE SPEED CONDITIONS

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Abstract
The paper has focused on the internal parameter designing of the hybrid electric vehicle operating in parallel hybrid condition and the performance according to various speeding condition is predicted through the linearly interpolated particle swarm optimization and further by the differential evolutionary algorithm. The analysis has been performed in the MATLAB/Simulink environment to record the performance of the vehicle. The predictive analysis has been found to be effective and therefore beneficial for determining the various components life at the time of different running conditions.

Keywords: hybrid electric vehicle, differential evolutionary technique, Speed, SOC, Prediction analysis

Introduction

In the near future, as concerns about climate change and air pollution continue to grow, more and more people are turning to hybrid electric vehicles as a way to reduce their carbon footprint and cut down on fuel costs. HEVs have become increasingly popular because they offer a number of advantages over traditional gasoline-powered vehicles. For example, they have better fuel efficiency and emit fewer greenhouse gases and other pollutants[1].

HEVs come in several different types, including parallel hybrids, series hybrids, and plug-in hybrids. Each type has its own unique characteristics and benefits. For example, parallel hybrids use both an internal combustion engine and an electric motor to power the vehicle, while series hybrids rely mostly on the electric motor with the internal combustion engine acting as a generator to charge the battery. Plug-in hybrids can be charged from an external power source and can operate in electric-only mode for a limited distance before switching to hybrid mode.

As more and more people adopt HEVs, the demand for charging infrastructure and battery recycling services will increase. Governments and private companies are likely to invest in these areas to support the growing market for HEVs. In addition, advances in battery technology will continue to improve the performance and range of HEVs, making them an even more attractive option for consumers. Overall, the future looks bright for HEVs as they continue to gain popularity and become a more common sight on the roads.

There are several types of hybrid electric vehicles (HEVs) available on the market. Here are a few examples:

- Full Hybrid Electric Vehicle (FHEV) - This type of HEV has both an electric motor and an internal combustion engine (ICE) that can be used to power the vehicle. FHEVs are capable of operating on electric power only, gasoline power only, or a combination of both. Examples of FHEVs include the Toyota Prius and the Ford Fusion Hybrid [1].
- Plug-in Hybrid Electric Vehicle (PHEV) - This type of HEV has a larger battery than FHEVs and can be charged by plugging it into an electrical outlet. PHEVs can operate on electric power only for a limited range, and then switch to gasoline power when the battery is depleted. Examples of PHEVs include the Chevrolet Volt and the Mitsubishi Outlander PHEV.
- Mild Hybrid Electric Vehicle (MHEV) - This type of HEV has a smaller battery and electric motor than FHEVs and PHEVs. The electric motor assists the gasoline engine during acceleration and provides regenerative braking to recharge the battery. Examples of MHEVs include the Honda Insight and the Hyundai Kona Hybrid.
- Range-extended Electric Vehicle (REEV) - This type of HEV has an electric motor and a gasoline engine that is used solely to generate electricity for the electric motor. The gasoline engine does not provide direct power to the wheels. Examples of REEVs include the BMW i3 with Range Extender and the Chevrolet Volt.

There are several types of hybrid electric vehicles (HEVs) available in the market, each with its own unique configuration and characteristics. Here are some common types of HEVs with references:

- Series Hybrid Electric Vehicle (SHEV): In SHEVs, the internal combustion engine is only used to generate electricity to power the electric motor, which propels the vehicle. Examples of SHEVs include the Chevrolet Volt and BMW i3 [1].
- Parallel Hybrid Electric Vehicle (PHEV): PHEVs use both the internal combustion engine and the electric motor to propel the vehicle. The two power sources can work together or separately, depending on driving conditions. Examples of PHEVs include the Toyota Prius and Honda Insight [2].
- Power Split Hybrid Electric Vehicle (PSHEV): PSHEVs, also known as Series-Parallel Hybrid Electric Vehicles, use a planetary gearset to split the power between the internal combustion engine and the electric motor. Examples of PSHEVs include the Toyota Prius and Ford Fusion Hybrid [3].
- Plug-in Hybrid Electric Vehicle (PHEV): PHEVs are similar to PHEVs, but with a larger battery that can be recharged by plugging in to an external power source. This allows PHEVs to operate in all-electric mode for a longer distance. Examples of PHEVs include the Chevrolet Volt and Mitsubishi Outlander PHEV [4].

It's worth noting that there are other variations of HEVs as well, including mild hybrid electric vehicles and range-extended electric vehicles. Each type of HEV has its own advantages and disadvantages, and choosing the right one depends on the specific needs and preferences of the driver.

The present study cover various aspects of hybrid electric vehicles, including energy management strategies, powertrain configurations, and recent developments in the field. They provide valuable insights into the performance, efficiency, and environmental impact of HEVs, and can be helpful for researchers, engineers, and policymakers working in the field

Modelling and simulation

The performance of a hybrid electric vehicle (HEV) can be predicted using a combination of simulation models and a predefined data set. The performance of an HEV depends on several factors, including the powertrain configuration, the size of the electric motor and battery, the energy management strategy, and the driving conditions. Simulation models are used in the present research to predict the performance of HEVs under different driving scenarios and operating conditions. These models can simulate the powertrain components, the energy flows, and the control strategies of the HEV, and can provide insights into the vehicle's efficiency, range, and emissions. Dataset used can be used to validate and refine the simulation models. Real-world testing of HEVs can provide data on fuel economy, electric range, acceleration, and other performance metrics. This data can be used to improve the accuracy of the simulation models and to optimize the design and control of HEVs. While HEVs are generally not as powerful as their gasoline-powered counterparts, they can still provide good acceleration and performance. As powertrain designs continue to evolve, it's possible that HEVs will become even more responsive and dynamic.

It is based on the success of all particles that emulates a population where the position of each particle depends to the agent position to detect the best solution P_{best} by using current particles in the population G. The position of any particle xi is adjusted by

$$x_i^{k=1} = x_i^k + v_i$$

where the velocity component vi represents the step size and is calculated by:

$$v_i^k = wv_i^k + c_1r_1\left(P_{best_i} - x_i^k\right) + c_2r_2(G - x_i^k)$$

where x is the inertial weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are random values that belong to the interval of [0, 1], $P_{best_i}$is the best position of particle i, and G is the best position in the entire population.

The Particle Swarm Optimization (PSO) algorithm involves a set of equations to optimize the performance of a hybrid electric vehicle (HEV) model. Here are the basic equations involved in PSO algorithm:

- Initialization: Initialize the position and velocity of each particle in the swarm randomly within the search space. The position vector xi of particle i contains the decision variables, while the velocity vector vi of particle i contains the corresponding velocities.
- Evaluation: Evaluate the fitness of each particle using the objective function. The fitness value is assigned to the particle's personal best value pi.
- Update personal best: Compare the fitness value of each particle to its personal best value. If the fitness value is better, update the personal best position pi of that particle.
- Update global best: Compare the fitness value of each particle to the global best value found so far. If the fitness value is better, update the global best position p*.
- Update velocity: Update the velocity of each particle based on its current velocity, personal best position, and global best position. The velocity vector of particle i at iteration k is updated using the following equation:

  $$v_i(k+1) = v * v_i(k) + c_1r_1 * \left(p_i - x_i(k)\right) + c_2r_2(p^* - x_i(k))$$

- where w is the inertia weight, c1 and c2 are the acceleration constants, r1 and r2 are random numbers between 0 and 1, pi is the personal best position of particle i, and p* is the global best position found so far.
- Update position: Update the position of each particle based on its updated velocity. The position vector of particle i at iteration k+1 is updated using the following equation: $x_i(k+1) = x_i(k) + v_i(k+1)$
- Termination: The algorithm terminates when a stopping criterion is met, such as reaching a maximum number of iterations or a satisfactory fitness value.

Using these equations, the PSO algorithm has optimized the performance of a HEV model by searching for the optimal values of the decision variables that minimize the objective function.

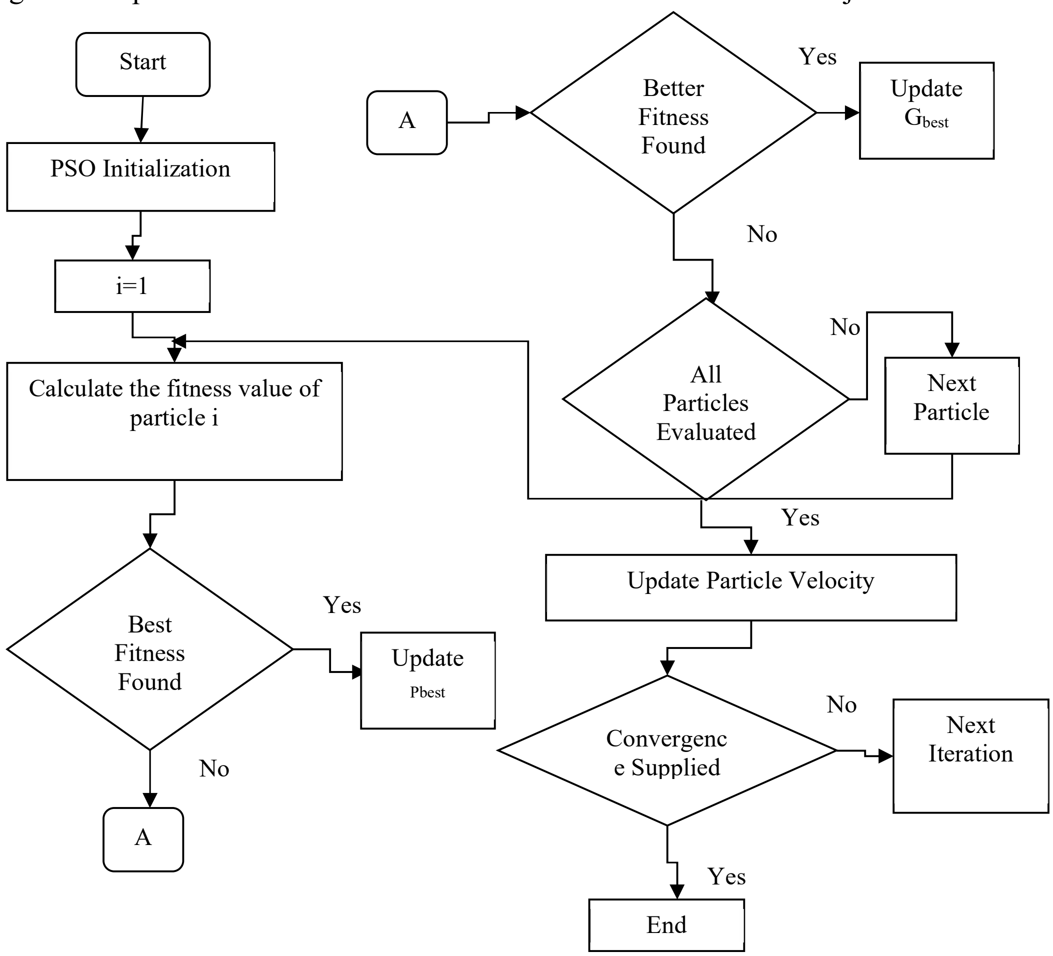


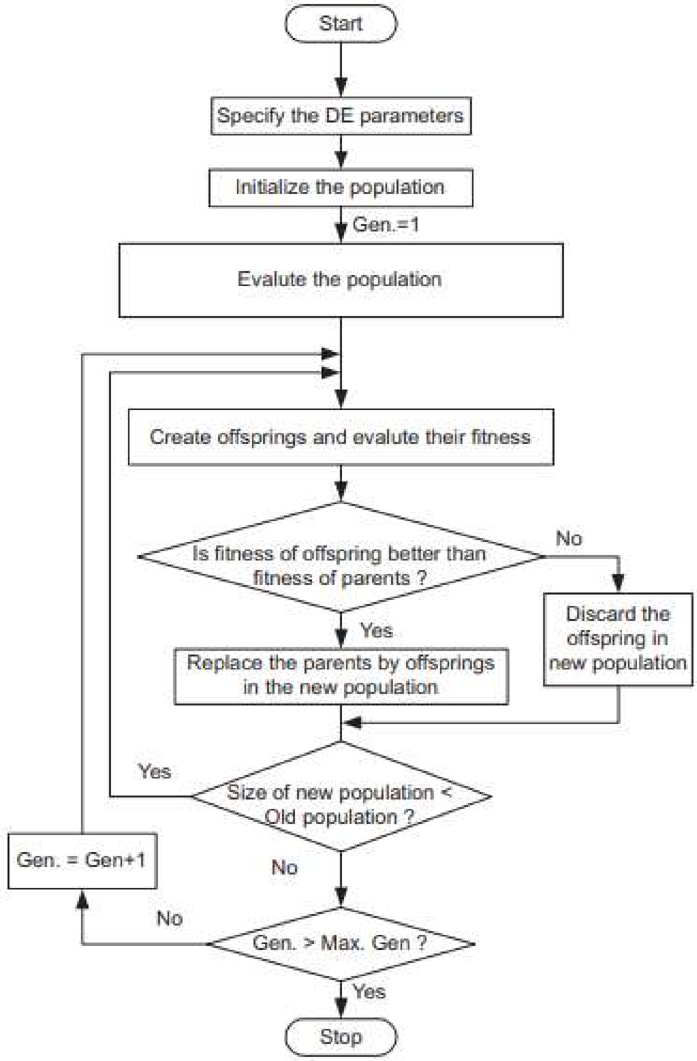
Figure 4.4: Linear PSO algorithm implementation for hybrid electric vehicle Technique

Differential Evolution (DE) is another metaheuristic optimization algorithm that can be used to predict the performance of a hybrid electric vehicle (HEV). Here is an example of how DE algorithm can be used for this purpose:

- Define the objective function: The objective function represents the performance metric to be optimized, such as fuel economy or emissions. In this case, the objective function could be defined as the total fuel consumption of the HEV over a driving cycle.

- Define the decision variables: The decision variables represent the design parameters of the HEV, such as the battery size and the size of the internal combustion engine. These variables are used to calculate the output of the HEV model.
- Setting of DE algorithm parameters: The DE algorithm has several parameters that need to be set, such as the population size and the crossover rate. These parameters can affect the convergence speed and the quality of the solution.
- Initialize the population: The population consists of a set of candidate solutions, each representing a possible set of values for the decision variables.
- Evaluate the fitness: Evaluate the fitness of each candidate solution by calculating the objective function.
- Selection: Select the best candidate solutions based on their fitness values.
- Mutation: Create a new generation of candidate solutions by applying the DE mutation operator to the selected solutions. The mutation operator generates a new candidate solution by combining the decision variables of two or more selected solutions.
- Crossover: Combine the mutated candidate solutions with the original candidate solutions using the DE crossover operator. The crossover operator selects a random component from the mutated candidate solution and replaces the corresponding component in the original candidate solution.
- Evaluate the fitness of the new population.
- Termination: The algorithm terminates when a stopping criterion is met, such as reaching a maximum number of iterations or a satisfactory fitness value.

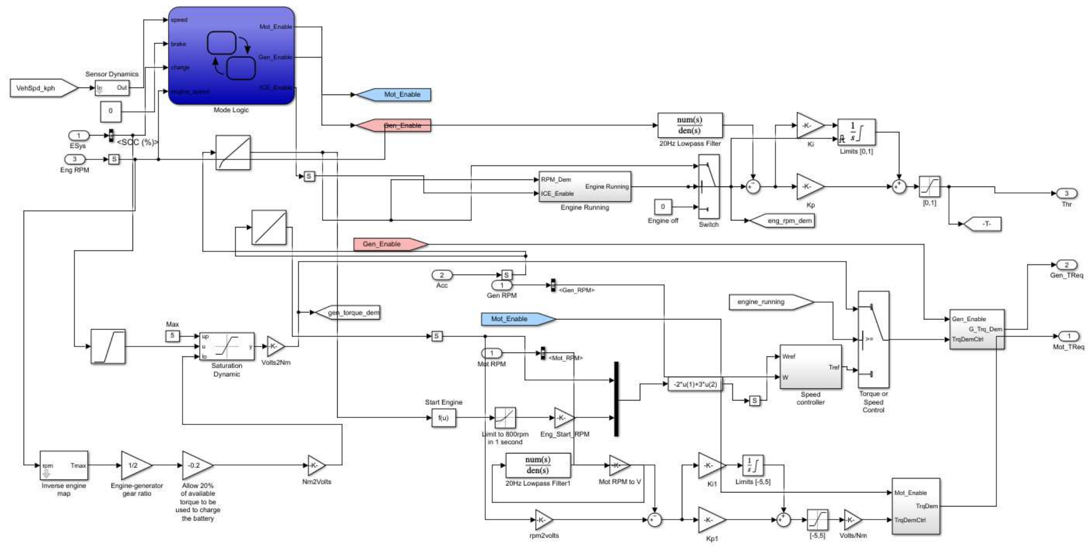
The DE optimizing algorithm coding and performance is carried out in the following steps as shown in flow chart below:



Flow chart of proposed Differential Evolutionary Algorithm for converters

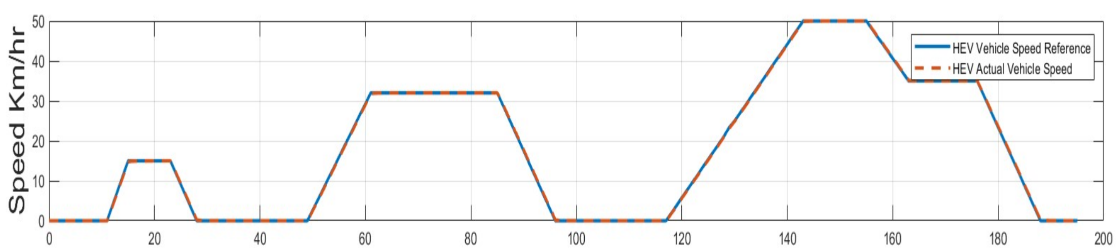
Differential Evolution (DE) is a population-based heuristic algorithm to solve global optimization problems with different characteristics over continuous space. Despite its simplicity, it proved a great performance in solving non-differentiable, non-continuous and multi-modal optimization problems. In simple DE, DE/rand/1/bin , an initial population of NP individuals $\overrightarrow{X_j}$, j=1, 2,.., NP , is generated at random according to aρ uniform distribution within lower and upper boundaries (x_j^L , x_j^U). Individuals are evolved by the means of crossover and mutation to generate a trial vector. The trial vector competes with his parent in order to select the fittest to the next generation.

The DE algorithm has proven to be able to optimize the performance of a HEV model by searching for the optimal values of the decision variables that minimize the objective function. It has the capability to handle both non-linear and non-differentiable objective functions, which are common in HEV modelling.

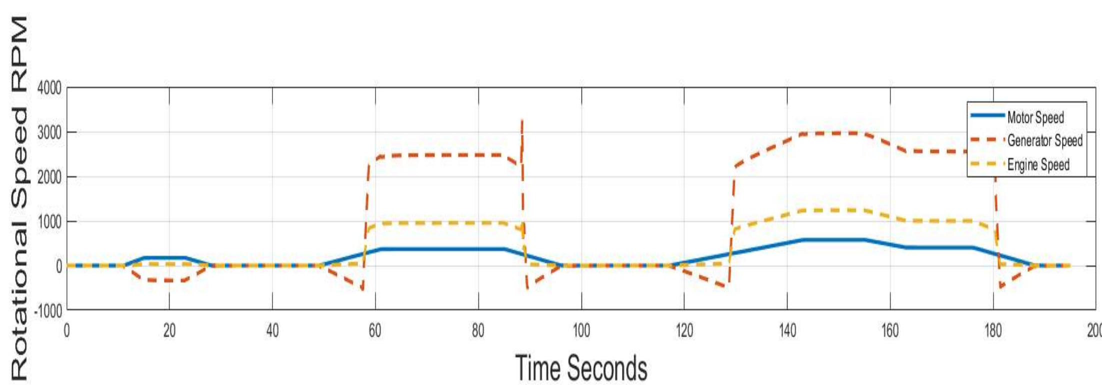


Control System Designing in MATLAB/SIMULINK to achieve the best prediction parameters

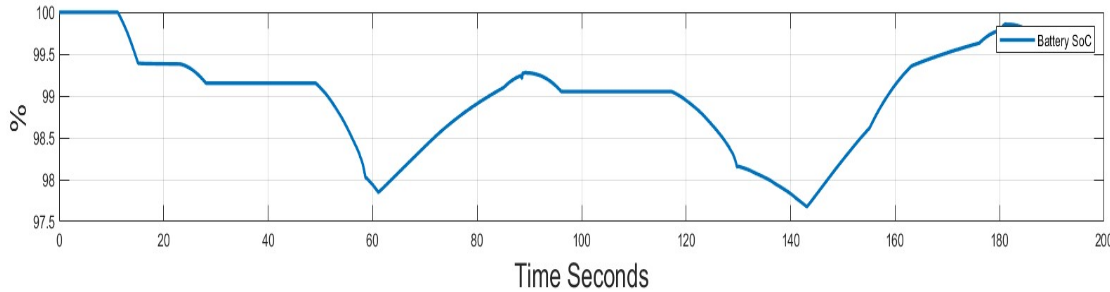
Simulation Outcomes



Speed refence given to the optimization controller of HEV



Speed refence of engine, motor and generator of HEV



Battery SOC % at the reference speed condition to the HEV

Conclusion

Overall, the performance of an HEV can be predicted based on the specific design and operating conditions of the vehicle. By using simulation models and dataset, the work has optimized the performance of HEVs and improve their overall efficiency and sustainability. The methodology proposed based on differential evolutionary algorithm has been shown to offer statistically significant improvement over other approaches. This implementation shows that the concept has the potential to be a powerful addition to evolutionary optimization algorithms.

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