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A Methodology to Design an Efficient EM Controller with High Practicability in HEVs Modeling and Optimization

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Abstract— **The energy management (EM) problem in hybrid electric vehicles (HEVs) has been extensively interested. Herein, a new approach to improve the EM control logic based on improving control-oriented operations of HEV system via deriving rules with considering the speed tracking feature is proposed. Thus, it leads to design of efficient EM strategies with high practicability. For this purpose, a novel methodology for implementing local search and evolutionary strategy optimization techniques in the EM problem is proposed. In order to realize the proposed method, a generic framework for modelling the HEV-system is proposed which has the desired flexibility and simplicity in implementing in the EM studies. In implementing the mentioned optimization techniques, by focusing on minimizing the overall fuel consumption and controlling the decision variables are taken as an optimization objective where a new heuristic procedure for human operation is proposed. Through computational examples with a series-parallel type on several pre-given driving missions, fuel consumption improvement with sufficient accuracy was observed and the effectiveness of the proposed approach in the finding the improved decision variables resulting in design of efficient EM strategies was confirmed.**

Index Terms— **Energy control system, energy management, evolutionary computing optimization, HEV systems, local search optimization.**

I. Introduction

The increased global energy demand with limitation in the fossil fuels and environment concerns has been one of the major challenges of the automotive industry which electrification of the automotive is the current focus to shift fossil fuel based transportation to alternative energy based transportation where various types of alternative vehicles with low or zero emissions is developing. A hybrid electric vehicle (HEV) essentially comprises a conventional combustion engine's propulsive system with one or more electrical propulsive systems. An HEV performance enhancement can be characterized by objectives such as improving fuel economy, reducing pollutant emissions, prolonging lifetime of electrical power source(s) (e.g. the battery), and enhancing vehicle drivability [1].

Under this background, a vehicle-level control system should be designed that can thoroughly realize the potential of HEV powertrains to meet the mentioned challenges. Management of splitting energy between energy sources in HEV, known as energy management (EM), has shown to result in the HEV performance improvement. Due to the flexibility of energy source selection in HEVs, one can expect that energy management strategies have significant influence on the HEV performance improvements.

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The EM system by such kind of control algorithms not only determines the proper power level to be generated, but also it is responsible to split power between energy sources. For this purpose, a controller is designed to meet the driver's power demand while improving HEV performance well-known EM controller. Generally, the output of the EM system can coordinate the overall powertrain to satisfy all or specific HEV performance, where it becomes the set-points for the control of the propulsive components.

Considering the scope of the dependency on the knowledge of future driving situations, including road conditions, driving conditions and personalized styles, the EM controller can be classified to non-causal and causal [2]. The former is based on the detailed knowledge of the future driving conditions for designing the EM controller where except in some specific cases, it is impossible to be implemented directly in the real driving. On the contrary, the causal controller is designed for practical driving situations without a prior full knowledge about the future driving situations. In this type of driving classification, the predictive information from driving situations in short and/or intermediate time is considered.

Another classification to apply the control algorithms in the EM system, i.e. in designing the EM controller, is heuristic methods, learning-based, and optimal control techniques [3]. The implemented strategies in the former class of controllers are knowledge-based which use rule-based or map-based approaches. The knowledge is based on the human experiences, the analysis of power flow in HEV, input-output functions and characteristics of the main propulsive components. These kinds of strategies show robustness with high degree of stability. However, they cannot completely achieve to optimize of the HEV performance. The reinforcement learning can improve the optimality of the HEV performance than previous approach. However, the optimality and learning are added together and make it difficult to be implemented real-time. The strategies obtained by optimal control approaches to maximizing the all or certain HEV performance via a predefined objective function are known as optimization-based energy management strategies. However, the optimal control techniques need the computational demand. The optimization process that leads to design non-causal controller is called offline optimization, whereas, the optimization process which takes the predictive information from driving situations into account, the predictive is called real-time optimization. The offline optimization is useful for benchmark real-time controller design or deriving rules based on optimal powertrain behavior observed in the optimal or near-optimal solutions. On the other hand, the exact demand prediction in the real-time controller is difficult, but, even if known, the state space is too large, and, therefore, some generalized treatments should be considered. These treatments make the energy management problem more complex [4].

The aim of this research is proposing a methodology to design efficient EM strategies via deriving rules with considering the speed-tracking feature that helps the complex behaviors caused by human drivers are negotiated and, hence, lead to design of the free-driving-characteristics EM controller preferably. For this purpose, the balance between optimality and implementation aspects should be considered by an equal level of attention. Otherwise it can cause negative effects on achieving high HEV performance in practical application. The suggested methodology can be applied to any kind of HEVs.

The main approach of this research is to join control actions based on some policies and utilization of optimization techniques where the information of the current state of the vehicle and, possibly, prediction of the future vehicle state is applied. This approach can lead to find a set of data that can be used for stable rules acquisition with appropriate optimality degree, hence, designing efficient EMS. In other words, the obtained results by this approach are control-oriented optimum.

Since the drawback of applying the strict optimization techniques in the EM problem is high computational complexity, the metaheuristic optimization techniques are the best solutions to apply in this approach. In this technique, one or more initial solutions are produced by heuristic methods then during optimization process they are optimized. Therefore, by using this approach, the optimum seeking process performs improvement of existing EM control logic. This paper specifically focuses on the obtaining this kind of improved solutions.

In addition to the issue mentioned above, one of the challenges of the model-based optimization is the complexity in computational experiments and, consequently, long computational time to simulate the HEV-system [5]-[6]. In other words, since a computational model represents the functionalities of a target system, minimum parameters for rules of model behavior or model properties that satisfy the sufficient accuracy for the EM studies is preferred. Therefore, a methodology for the HEV modelling to set the EM problem is proposed.

Throughout this research, it is assumed that the HEV performance is only focused on the fuel economy level. Although, the dimensioning of the powertrain is fixed and sizing is consequently not considered in the problem formulation. Furthermore, the predictive driving situations are not also treated explicitly. The energy management optimization is performed with a deterministic representation of the driving conditions by the proposed original approach to optimize control operations to improve the reliability of the strategies. It is realized by two novel methods local search and evolutionary search techniques. A case study considering above settings for a series-parallel structure would be constructed. The results of computational experiments reveal the improved control behavior for the EM strategies. The ideas presented here are applicable on any HEV structure. However, results are shown for a specific sample HEV.

This paper is organized as follows: Section II states the complete HEV modelling. In the section III, the EM problem formulates as a constrained finite-time optimization problem and the proposed control techniques are briefly introduced. The proposed LS search strategies are implemented by a new heuristic approach in section IV. Section V realizes a new evolutionary strategy in the EM optimization problem. The simulation environment, the vehicle implementation, and an overview of the results are presented in section VI. Finally, conclusions are given in section VII.

II. Vehicle Modelling

According to the structures recently developed for HEV systems, an HEV simplifies several main propulsive components, that a complete model of HEV comprises a combination of models of these components. The aim of modeling is analytically and numerically to setup the EM problem, with appropriate accuracy and computational cost considerations. The modeling process should yield to create the general models of components that clearly represents actual energy flows. Using modular approach, combining the models of components to represent any structure is straightforward. In the following, a new method for modelling of a complete HEV based on new simplified models of main propulsive components is proposed. The specifying characteristics an appropriate modelling are as follows:

1) Generalization for a wide range of HEVs where various arrangements of the HEV components can be modeled by the same basic components models and causes to consist of functionalities of system.

2) Flexibility in utilization for optimization and learning techniques by reasonable low computational cost.

3) Suitable for the EM studies. It means they should have sufficient accuracy for the energy flow studies in HEVs.

Fig. 1 shows an overall physical model consists of the main propulsive components of HEVs. The input of the HEV-system is fuel mass (m_{f}) and the output is the linear speed (V) of vehicle.

The main propulsive components for modeling process are

- Internal combustion engine
- Electric machine (EM)
- Electrical energy storage (EES)
- Mechanical transmission
- Electrical BUS
- Power splitter (PS)

Each component is represented by input and output ports and as well as some additional parameter(s). As can be seen in Fig. 1, in each port of components, the torque at mechanical side and the current at electrical side are directly transferred between propulsive components. Therefore, the output power of components is equal to the input power of adjacent components. In addition, the representation of the speed in two adjacent components in mechanical areas are considered as mathematical representation with equal together. However, really, they do not treat as input-output in the

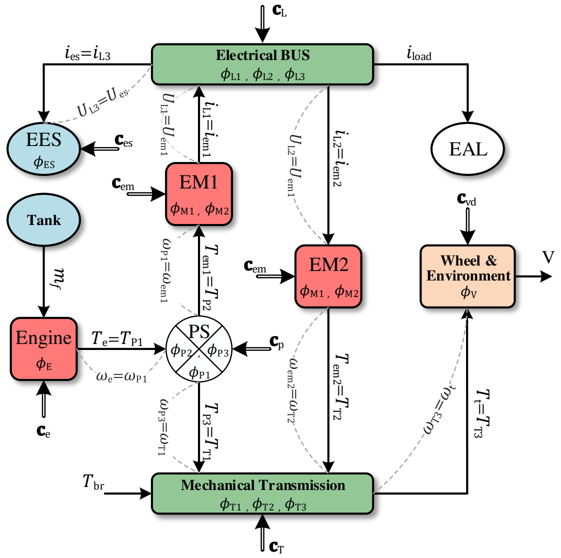

Fig. 1. Physical model of HEV with two energy sources.

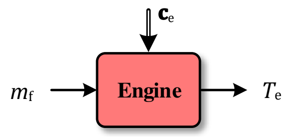

Fig. 2. Physical model of the engine.

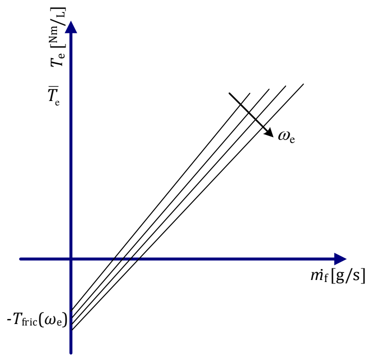

Fig. 3. Linearized relation of the engine input/output interfaces.

components. To model the HEV-system such simplifications should be considered corresponding to the flexibility in utilization for the EM problems while conserving the computational accuracy. Taking the mentioned characteristics, the main considerations into account, and assumptions are

- Using quasi-static mathematical model with a linear relation for representing input/output of the engine and as well as a first order dynamic model for estimating the speed of the engine;
- The extra fuel consumption during the cranking phase and thermal effects of the engine are negotiable. All driving situations start with a pre-heated engine;
- Using static model for characterizing electric machine(s) by electrical-mechanical system equations;
- Using a linear model derived from the electrical circuit model for representing the battery;
- Using a first order dynamic model for estimating the charge status of battery;
- Using quasi-static model to representing the energy flow in electrical BUS, mechanical transmission and power splitter;
- Time-invariant splitter and transmission ratios in power splitter and mechanical transmission, respectively;
- No dynamic effects on power splitter, mechanical transmission, electrical BUS and wheel;
- The head wind speed is negotiable.

A. Engine

An engine as a fuel converter is an inevitable component in the HEVs. As is shown in Fig. 2, the fuel is the only input of the engine that is converted to torque at output interface.

The input-output function ϕ_{E} of engine is described as

$$T_{\mathrm{e}} = \phi_{\mathrm{E}}(\dot{m}_{\mathrm{f}}, \omega_{\mathrm{e}}, \mathbf{c}_{\mathrm{e}}) \tag{1}$$

where T_{e} is the output torque, $\dot{m}_{\mathrm{f}}$ is the fuel mass rate, ω_{e} is the velocity of the engine shaft and $\mathbf{c}_{\mathrm{e}}$ is the set of engine parameters. In reference [7] is proposed a simplified equation as transformation gain for the engine is shown in Fig. 3. The linearized relation of the input/output is expressed by

$$T_{\mathrm{e}} = \frac{\dot{m}_{\mathrm{f}}}{c'_{\mathrm{e}}\omega_{\mathrm{e}}} - T_{\mathrm{fric}}(\omega_{\mathrm{e}}) \tag{2}$$

where c'_{e} is a coefficient and is equal to 6.67×10^{-5} and T_{fric} is the friction torque which is a function of the engine velocity. The friction torque is approximated by a linearized relation. At idle speed, it is equal to around eight [Nm/L] and at the maximum speed of the engine it is increased to around the 16 [Nm/L].

The engine speed can be governed by a low-order dynamic equation based on Newton's law and is expressed as

$$\dot{\omega}_{\mathrm{e}} = \frac{1}{J_{\mathrm{e}}}(T_{\mathrm{e}} - T_{\mathrm{l}}) \tag{3}$$

where J_{e} is the moment of inertia and T_{l} is the effective torque.

B. Electric Machine

The electric machines are bidirectional energy converters, i.e. the current (i_{em}) is converted to the torque (T_{em}) or vice versa which is well-known generator or motor, which the motor operation is sketched in Fig. 4 and mathematically expressed by the function ϕ_{M1} as

$$i_{\mathrm{em}} = \phi_{\mathrm{M1}}(T_{\mathrm{em}}, \mathbf{c}_{\mathrm{em}}) \tag{4}$$

where the ($\mathbf{c}_{\mathrm{em}}$) denotes the additional parameters set. These parameters ($\mathbf{c}_{\mathrm{em}}$) depend on the type of the machine. In reference [7] is also proposed a simplified mathematical model for electric machines for HEVs. This relation is based on the systemic equations of the DC machines that described as (5) and (6).

$$T_{\mathrm{em}} = K_{\mathrm{em}} i_{\mathrm{em}} \tag{5}$$

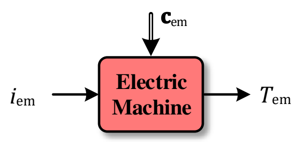

Fig. 4. Physical model of the electric machine.

$$U_{\mathrm{em}} = \phi_{\mathrm{M2}}(i_{\mathrm{em}}, \omega_{\mathrm{em}}) = R_{\mathrm{em}} i_{\mathrm{em}} + K_{\mathrm{em}} \omega_{\mathrm{em}} + L_{\mathrm{em}} \frac{\mathrm{d}i_{\mathrm{em}}}{\mathrm{d}t} \quad (6)$$

where K_{em} denotes the back-EMF constant and R_{em} is the internal resistance and L_{em} is the inductance of the armature winding with eliminating the field and mechanical losses. U_{em} denotes the terminal voltage and ω_{em} is the velocity of shaft. As the viewpoint of quasi-static modeling, the power at electrical side ($P_{\mathrm{em,e}}$) instead of machine current is preferred and calculated from

$$P_{\mathrm{em,e}} = i_{\mathrm{em}} U_{\mathrm{em}} = T_{\mathrm{em}} \omega_{\mathrm{em}} - \frac{R_{\mathrm{em}}}{K_{\mathrm{em}}^2} T_{\mathrm{em}} \quad (7)$$

C. Electrical Energy Storage

A suitable electrical energy storage (EES) to assist the prime mover is batteries that nowadays favored and promoted for the HEVs. The affected parameters ($\mathbf{c}_{\mathrm{es}}$) on input-output characteristics are the polarization capacitive effect, incipient capacitance of the battery, internal battery resistance, and terminal ohmic resistance [8]. The battery saves the current (i_{es}) as only input without any output that is shown in Fig. 5. It means the battery can treat as a reservoir in the HEVs.

A mathematical function (ϕ_{ES}) indicates the relation between terminal voltage U_{es} and the current as

$$U_{\mathrm{es}} = \phi_{\mathrm{ES}}(i_{\mathrm{es}}, \mathbf{c}_{\mathrm{es}}) \quad (8)$$

Generally, modeling of the behavior of battery is done by the electrical circuit model approach. The most common model in the EM studies is linear model without any dynamics. The model consists of an ideal-battery with open-circuit voltage (U_{oc}) and an equivalent internal resistance (R_{b}), as can be seen in Fig. 6. The input-output equation based on the linear model is

$$U_{\mathrm{es}} = U_{\mathrm{oc}} - R_{\mathrm{b}} i_{\mathrm{es}} \quad (9)$$

In order to consider the varying characteristics of the battery in model, the open-circuit voltage and internal resistance may be related on the state of charge (SoC) and battery temperature. Simpler models are often used without any dependencies. Therefore, the SoC of the battery (C_{b}) is given by a simple low-order dynamic equation using the input parameter of the battery by in form

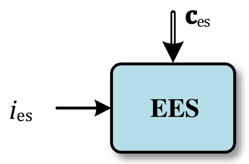

Fig. 5. Physical model of the electrical energy storage system.

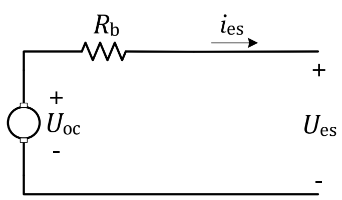

Fig. 6. Equivalent circuit model for the ideal battery.

$$\dot{C}_{\mathrm{b}} = -\frac{i_{\mathrm{es}}}{Q_{\mathrm{b}}} \quad (10)$$

where Q_{b} is the battery capacity. The power of battery at terminal is expressed from substituting the (9) on the power law equation as

$$P_{\mathrm{b}} = U_{\mathrm{oc}} i_{\mathrm{es}} - R_{\mathrm{b}} i_{\mathrm{es}}^2 \quad (11)$$

According to the current arrow in Fig. 6, the P_{b} and i_{es} are both positive, the battery is in discharging mode. Instead of determining the battery current for calculating the SoC, the (10) and (11) can be integrated. Thus, a relation between SoC and the battery power is yielded as

$$\dot{C}_{\mathrm{b}} = -\frac{U_{\mathrm{oc}} - \sqrt{U_{\mathrm{oc}}^2 - 4P_{\mathrm{b}} R_{\mathrm{b}}}}{2Q_{\mathrm{b}} R_{\mathrm{b}}} \quad (12)$$

D. Mechanical Transmission

The mechanical transmission on vehicles combines the torques from different mechanical links that the sketch is depicted in Fig. 7. The input-output torques for four ports are expressed by

$$T_{\mathrm{T3}} = \phi_{\mathrm{T1}}(T_{\mathrm{T1}}, T_{\mathrm{T2}}, \mathbf{c}_{\mathrm{T}}, \eta_{\mathrm{T}}, T_{\mathrm{br}}) \quad (13)$$

where T_{br} denotes the negative torque by brakes. $\mathbf{c}_{\mathrm{T}}$ is the transmission ratio's set that they are only endogenous parameters ($\mathbf{c}_{\mathrm{T}} = \{c_{\mathrm{T1}}, c_{\mathrm{T2}}\}$). η_{T} is efficiency of the transmission part that is usually modeled as a constant. This function can be formulated as

$$T_{\mathrm{T3}} = \eta_{\mathrm{T}}(c_{\mathrm{T1}} T_{\mathrm{T1}} + c_{\mathrm{T2}} T_{\mathrm{T2}}) - T_{\mathrm{br}} \quad (14)$$

The speed relations between ports are expressed by

$$\omega_{\mathrm{T1}} = \phi_{\mathrm{T2}}(\omega_{\mathrm{T3}}, c_{\mathrm{T1}}) = c_{\mathrm{T1}} \omega_{\mathrm{T3}} \quad (15)$$
$$\omega_{\mathrm{T2}} = \phi_{\mathrm{T3}}(\omega_{\mathrm{T3}}, c_{\mathrm{T2}}) = c_{\mathrm{T2}} \omega_{\mathrm{T3}} \quad (16)$$

E. Electrical BUS

The electrical bus matches the voltage level of the EES with the auxiliary loads (EAL) and the electric machines by some power electronics modules that sketched in Fig. 8.

Usually, the auxiliary loads are modeled as a lumped load and equal to a constant. The balance equation of currents flowing across the electrical BUS for four ports can be expressed by below function.

$$i_{\mathrm{L3}} = \phi_{\mathrm{L1}}(i_{\mathrm{L1}}, i_{\mathrm{L2}}, \mathbf{c}_{\mathrm{L}}, \eta_{\mathrm{L}}, i_{\mathrm{Load}}) \quad (17)$$

where η_{L} is the efficiency of the power electronics module (inverter/converter). The $\mathbf{c}_{\mathrm{L}}$ is the set of voltage ratios ($\mathbf{c}_{\mathrm{L}} = \{c_{\mathrm{L1}}, c_{\mathrm{L2}}\}$). Thereby, the balance equation is

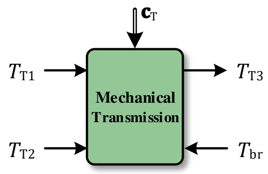

Fig. 7. Physical model of the mechanical transmission.

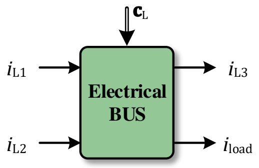

Fig. 8. Physical model of the electrical BUS.

$$i_{L3} = \eta_L(c_{L1}i_{L1} + c_{L2}i_{L2}) - i_{Load} \tag{18}$$

The voltage ratios are controlled and determined by the duty cycle of the power electronic devices, however, with reasonable accuracy the characteristics of components at electrical side can be specified by the power. Therefore, the power balance across the electrical BUS for quasi-static representation is

$$P_{L3} = P_{L1} + P_{L2} - P_{Load} \tag{19}$$

where P_{Load} is the lumped power of the electric loads.

F. Power Splitter

The power splitter separates the torque at output ports with the splitter ratios ($\mathbf{c}_P$). The mathematical functions for three ports are stated by

$$T_{P2} = \phi_{P1}(T_{P1}, \eta_P, c_{P1}) \tag{20}$$
$$T_{P3} = \phi_{P2}(T_{P1}, \eta_P, c_{P2}) \tag{21}$$

where η_P is the efficiency of the power splitter. The torque equation at two ports of power splitter is related by two splitter coefficients as

$$T_{P2} = \left(\frac{c_{P1}}{c_{P1} + c_{P2}}\right)\eta_P T_{P1} \tag{22}$$
$$T_{P3} = \left(\frac{c_{P2}}{c_{P1} + c_{P2}}\right)\eta_P T_{P1} \tag{23}$$

The splitter coefficients are the number of teeth of output gears. The c_{P1} is the number of teeth of second port and the c_{P2} is the number of teeth of third port. The speed equation at three ports is expressed by

$$\omega_{P1} = \phi_{P3}(\omega_{P2}, \omega_{P3}, c_{P1}, c_{P2}) \tag{24}$$

The ratio of the relative speeds of the ports is defined as

$$\frac{\omega_{P3} - \omega_{P1}}{\omega_{P2} - \omega_{P1}} = -\frac{c_{P1}}{c_{P2}} \tag{25}$$

G. Wheel and Environment

The output of the HEV system is calculated by a non-linear dynamic model that so-called vehicle dynamics. The vehicle dynamics are classified into two sections; tire dynamics, and body dynamics. The (26) shows this governing function expressed by second law of Newton without any dynamics effects on tires.

$$\dot{V} = \phi_V(V, T_t, \mathbf{c}_{vd}) \tag{26}$$

where $\mathbf{c}_{vd}$ is the parameters set of vehicle body and wheel and V is determined by

$$V = r_w \omega_t \tag{27}$$

where r_w denotes the radii of the wheel and ω_t is the rotational speed of axle. As the viewpoint of simplicity, the function (ϕ_V) with considering the rolling and hill climbing resistances and aerodynamic drag is expressed by

$$\dot{V} = \frac{T_t}{r_w m_V} - \left(\frac{1}{2m_V}\rho A c_d V^2 + g_e(c_r \cos\theta + \sin\theta)\right) \tag{28}$$

where m_V denotes the total weight of vehicle and ρ is the density of the ambient air and is simply assumed constant. A is the frontal area of the vehicle; c_d is approximately constant that is called the aerodynamic drag coefficient; g_e is the gravity acceleration due to the gravity; c_r is the rolling friction coefficient and, finally, θ is the angle of the driving surface.

H. Model Evaluation

The mentioned framework for the modeling of the HEV system was realized on a series-parallel HEV equipped with a simple planetary gear train. The simulation was run with speed-tracking feature based on the power follower rule-based control strategy as a kind of canonical no optimized strategy. The simulation software is Matlab by Corei5-4258U processor and 4GB-DDR3 RAM.

The connection of simple planetary gear train is the same as Toyota Hybrid System (THS) so that the first port is related to the carrier, the second port is connected to the sun gear, and the third port is related to the ring gear. The proportion of the gears teeth is $c_{P2}/c_{P1} = 2.6$. The Figs. 9a and 9b show the characteristics of the studied engine with the proposed model. Additionally, the characteristic of the studied EM2 is shown on the Fig. 10.

It takes approximately 1.5 seconds to run the model to trace NEDC based on mentioned computational resources that is significantly lower than the model provided for JSAE-SICE Benchmark Problem II [9].

III. EM Problem Definition

As mentioned before, the output of HEV is linear speed. If the dynamic of HEV-system represented by the physical model, the fuel mass, as input of HEV-system, can determines the time series of final linear speed. Therefore, the time series of solution variables are fuel mass sequence during driving mission that an optimal fuel mass sequence leads to energy efficiency improvement.

In optimization-based energy management of the HEV-system, theoretically, the decision variable(s) can be chosen freely. Generally, the aim of the EM problem optimization, is finding the time series of the optimal or near-optimal decision variable(s) by seeking in search space that with the input of the HEV-system is different.

Furthermore, for finding an optimal or near-optimal solution at level of the physical model, i.e. fuel mass, applying some heuristic method is inevitable. The performance and possibility of the heuristic method is very important and is related to the assumptions and hypothesis considered for heuristics design. If the chosen decision

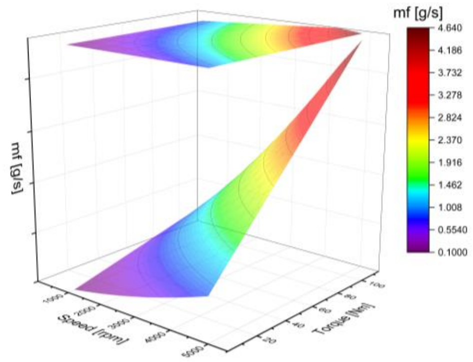

Fig. 9a. Fuel consumption of the studied engine.

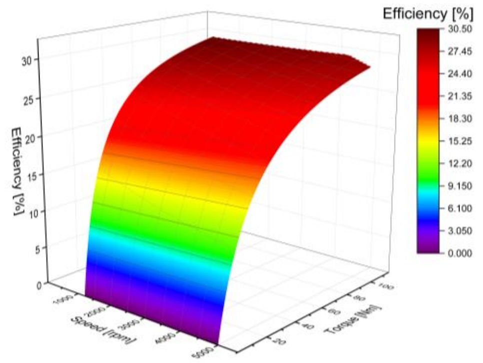

Fig. 9b. Energy efficiency of the studied engine.

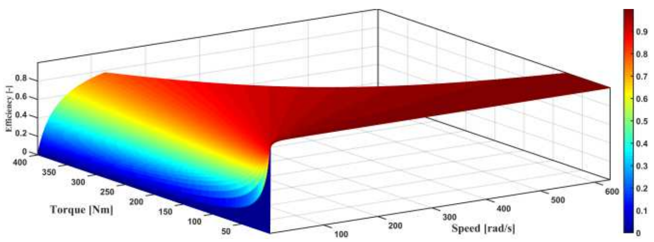

Fig. 10. Energy efficiency of the studied EM2.

variable(s) are near output variable, the degree of responsibility of heuristic will be higher. For example, according to the proposed complete HEV model, if the output torques of engine (T_e) and the EM2 (T_{em2}) selected as decision variables, the output of optimization with a prescribed driving cycle, is a time-series of optimal or near-optimal sequence of these decision variables. In each time span, the target is the calculation of the fuel mass (m_f). By using the reverse of the proposed mathematical functions on the EM1, the EM2 and the engine, the improved time-series of fuel mass under entire driving mission is determined, see Fig. 11. Consequently, selection of the variables near input of HEV-system causes to increasing the performance of heuristic function, however, this issue is beyond the scope of this research.

Nevertheless, the main objective for the EM optimization problem under a prescribed and arbitrary driving mission is reducing the total fuel consumption during overall driving mission. The EM optimization problem is formulated as

$$\min_{u} \quad J = \int_0^{t_f} \dot{m}_f(u(t), t)\mathrm{d}t \qquad \text{s.t.} \quad \mathbf{g} \leq \mathbf{0} \tag{29}$$

During the offline optimization process, the output of the HEV-system can be shifted to the upper level, i.e. required torque, on the output of mechanical transmission area (T_{T3}) and by knowing the required load, it can be determined. According to the proposed complete HEV model, the objective function can be expressed by other variables.

The main inequality constraints comprise to the state of charge of battery and the physical limitations of the main propulsive components. Other constraints could be included to some drivability or comfort issues. This makes the EM problem as a constrained finite-time optimization problem.

A. *Applied optimization techniques*

In this work, two model-based optimization techniques are realized. The first idea is local search optimization technique by two proposed search strategies that will be explained in section IV. In this technique, the searches are limited to narrow subsets and the search space is restricted on a grid. The next idea using the global search methods for solving the EM optimization problem to find the overall optimum and to avoid attraction of local optima. For realizing this idea, an evolutionary algorithm will be descripted in section V.

In the two proposed optimization techniques, the driving cycle is discretized that the length of the driving cycle is

$$n = \left\lceil \frac{t_f}{\Delta t} \right\rceil \tag{30}$$

where t_f is the total time of driving and Δt is the sample interval. Since the sample interval Δt is fixed, the signals are kept constant in between. Therefore, n is the dimension of the problem.

The two proposed optimization techniques in this work seek around current solution. At the first of optimization process, the initial solution can be obtained by heuristic methods and that is referred to control behaviors. To diversify for initial solution, it can be generated by Gaussian random distribution based on some principles and policies to move to feasible domain. The below principles are considered for producing initial solution.

- If the maximum output power of the battery is higher than the required traction power, the engine doesn't need to turn on.
- The required power for traction of the vehicle should be supplied in overall driving.

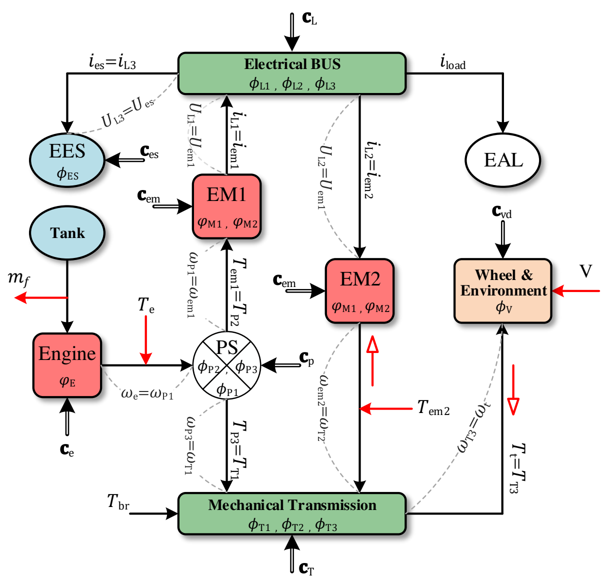

Fig. 11. A simplified example to obtain the improved solution.

- Keeping the generated solution in the feasible domain where the all constraints satisfied.
- During the deceleration or braking mode, the engine is turn off and the tractive electric machine as possible as saves the kinetic energy on the battery.

Furthermore, the desired policies are

- During standstill, if the SoC is lower than reference SoC the engine is turn on at idle speed with as possible as maximum efficiency.
- During deceleration or braking the EM2 as possible as absorbs the kinetic energy and stores in the battery.
- During moving forward
  - If the battery can be solely supplied the required power, the engine is turn off. In this condition, if the SoC is lower than its minimum allowable value, the engine should be turned on and operated as possible as with the high efficiency and maximum allowable torque such that can charge the battery and supply the required power for traction until the SoC reaches to the reference value.
  - When the demanded power is greater than the maximum output battery power, the engine is used to produce power while the battery assists the engine for supplying the required tractive power.

IV. Local Search

The local search (LS) is one kind of the metaheuristic techniques, which can locally search optimum point of the objective function of HEV-system for finding the optimal or near-optimal solution [10]. It means local search process is to seek better solutions in the neighbor of current solution. To implement the LS technique, the search space ($\mathcal{S}$) is discretized such that only levels between $\underline{\mathcal{S}}$ and $\overline{\mathcal{S}}$ will be used. The $l+1$ search levels are considered by

$$l = \left\lceil \frac{\overline{\mathcal{S}} - \underline{\mathcal{S}}}{\Delta s} \right\rceil \tag{31}$$

where Δs is the step size. The process of the multistage decision problem is established as following: at each time instant, the LS seeks in the search space ($\mathcal{S}$) and try to find feasible solutions in the current solution neighborhood.

A. LS utilization framework

Neighborhood structure: The neighborhood structure is constructed in two-dimensional space; the one or more search; i.e. decision, variables which makes a k-tuple and those levels (l) in their feasible boundaries. Therefore, the neighbor of each solution is defined by changing one or more k search variables in l levels while other variables are fixed. The neighborhood function is defined as

$$N(\mathbf{s}) = \{\mathbf{y} | y(j) = S(j),\ j \neq j^h,\ y_{j^h} = S_{j^h} \pm \sigma\Delta s\} \tag{32}$$

that

$$j = 1, \dots, n, \quad j^h = 1, \dots, n, \quad \sigma = 1, \dots, \lfloor 0.5l \rfloor$$
$$h = 1, \dots, k, \quad \mathbf{y} = \{y(1), \cdots, y(n)\}$$

On the other words, $\mathbf{y}$ can be obtained from $\mathbf{s}$ by changing k search variable(s) from the set $\mathbf{s}$. Finally, the neighborhood space is produced by $(l+1)^k - 1$ moves from current solution. Fig. 12 illustrates a simplified example with two successive search variables ($k = 2$) on two levels ($l = 2$). The total moves equal to eight that creates the neighbors' population.

Search strategy: Obviously, the exhaustive search or enumerating all of combination of sample moments is not possible and as well as not effective. Two search strategies are proposed in LS optimization technique that cause to reduce the amount of computations while there is a hope that the accuracy stays good enough.

Strategy 1 - In each search iteration, if $S(m)$ is the immediate predecessor of $S(m+1)$ until $S(m+k-1)$ in search order, the below combination of k search variable(s) possible selection can be viewed as

$$\{\langle S(1), \dots, S(k)\rangle, \dots, \langle S(m), \dots, S(m+k-1)\rangle, \dots \\ , \langle S(n), \dots, S(k-1)\rangle\} \tag{33}$$

Each chevron defines a k-tuple and used as a seed for searching process based on neighborhood function.

Strategy 2 - The main objective of this strategy finding some search variable(s) which potentially can be lead to find near-optimal solution that significantly cause to reduce the computational time than that of the previous search strategy. The selection process affected by some heuristic policies as

- During deceleration or braking, the engine is turn off and, obviously, the search on these stages cannot achieve in evaluation of objective function.
- Two parameters; the engine torque and the engine speed mathematically affect the fuel consumption. Achieving in evaluation process is affected by decreasing the engine speed. Therefore, as possible as, by changing the combination of search variables, which have the highest engine speed and the lowest engine speed, the candidate solution may have better objective function value.
- The stages that the engine is turn off have low priority for search to find near-optimal solution.

In each search iteration, a k-tuple is created by k search variables and the neighbor feasible solutions are found to evaluate with the current solution.

Finally, one can be expected that these search strategies lead to improve the computational time of running the LS. However, the length of driving cycle and the grid density have a negative effect on the number of computations.

B. LS Optimization Process

In each search iteration, some search variables are selected

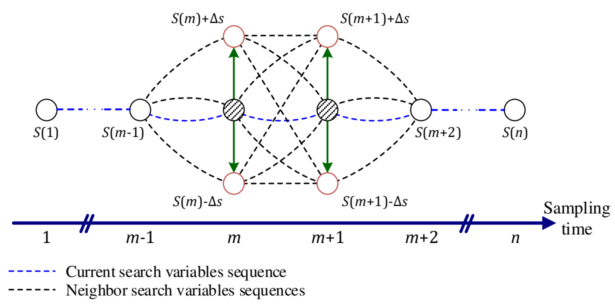

Fig. 12. Total moves in the simplified example.

that according to the neighborhood function, they can be switched to adjacent values while other search variables are fixed. Then, the new neighbor solutions are used to modelling and, hence, are evaluated. If new near-optimal solution is found, the procedure is restarted and again the search process is run on new near-optimal solution. Otherwise, the next nominated search variables are selected and so on. The mentioned process is repeated until the stop criterion is satisfied, i.e. no reasonable improving in the fuel economy.

V. Evolution Strategy

In this section, an evolution strategy that is a kind of evolutionary algorithm which inspired by the model of organic evolution, for solving the EM optimization problem will be introduced. The implemented search strategy approach in this technique is based on producing a better (offspring) solution by purposeful mutation in parent solution. The realized algorithm in this work is called (1+1)-ActiveCMA was developed the (1+1)-Cholesky-CMA algorithm [11] using the idea of the Active-CMA to take information of unsuccessful offspring into account for Cholesky factor adaptation [12]. This algorithm uses a mutation operator based on a multivariate normal distribution without any recombination operator for producing the offspring and based on an elitist selection method the new parent solution is selected. This strategy uses a self-adaptation approach for updating the covariance of the Gaussian distribution by a linear transformation and a metric parameter in the search process. For reducing the computational time, this algorithm directly works with the Cholesky factor.

The implemented algorithm is a two-membered evolution strategy. It means the population size of parent is one and, in each generation, only one offspring is produced. Therefore, the evaluation process according to the performance index of optimization problem between these solutions are run.

A. ES Utilization Framework

The elements of the proposed algorithm can be formalized using the evolutionary algorithm operator's framework. In the following, the operators will be described.

1) Mutation and Sampling

The mutation operator performs in two steps. First, the standard normal distribution is sampled to generate an n-dimensional random vector $\mathbf{z}$, where $\mathbf{z} \in \mathbb{R}^n$. Second, using a linear transformation for rotating and scaling of this vector is known as Cholesky factor $\mathbf{A}$, where $\mathbf{A} \in \mathbb{R}^{n\times n}$. This factor determines the shape of the distribution. Therefore, mutation vector is

$$\mathbf{A}^{(g)}\mathbf{z}^{(g)} \qquad \text{for } \mathbf{z}^{(g)} \sim \mathcal{N}(\mathbf{0},\mathbf{I}) \tag{34}$$

The basic equation for sampling the search points to procreate an offspring $\mathbf{u}_\mathrm{o}^{(g)}$, for generation number $g \geq 1$ is

$$\mathbf{u}_\mathrm{o}^{(g)} = \mathbf{u}_\mathrm{p}^{(g)} + \sigma^{(g)}\mathbf{A}^{(g)}\mathbf{z}^{(g)} \tag{35}$$

where, at generation g, $\mathbf{u}_\mathrm{p}^{(g)}$ is the vector-valued parent solution ($\mathbf{u}_\mathrm{p} \in \mathbb{R}^n$) and $\sigma^{(g)}$ is a scalar-valued step size can improve the sampling process for producing the offspring that so-called mutation strength. This parameter improves the convergence rate of the algorithm. Now, the set of vector-valued search point, the mutation strength and the Cholesky factor create a tuple that so-called individual is represented as $\langle \mathbf{u}, \sigma, \mathbf{A} \rangle$.

The Cholesky factor and the mutation strength are adaptable endogenous strategy parameters. The initial Cholesky factor is the unity matrix. The initial of the search point ($\mathbf{u}_\mathrm{p}^{(1)}$) is obtained by the randomly generated heuristic initial solution that was introduced in section IV. The typical initial mutation strength is one that during computations decreased.

2) Selection Operator

According to the objective of optimization problem, an elitist selection by considering one individual for an evaluation with parent solution is used. The parent solution for next generation is selected as

$$\mathbf{u}_\mathrm{p}^{(g+1)} := \begin{cases} \mathbf{u}_\mathrm{o}^{(g)}, & \text{if evaluation succeeded} \\ \mathbf{u}_\mathrm{p}^{(g)}, & \text{otherwise} \end{cases} \tag{36}$$

The offspring candidate solution is allowed to survive in overall generations. This strategy causes to keep the best solution found so far in the population. In the proposed algorithm, no recombination is used.

3) Updating Endogenous Strategy Parameters

After evaluation process, the mutation strength and the Cholesky factor and its inverse should be updated for next generation that so-called self-adaptation process. Note that the update of the Cholesky factor only changes the time scale in a single direction. The updating mutation strength leads to improve search convergence.

Adapting the Cholesky factor: In each generation, depending on the result of evaluation process, the Cholesky factor $\mathbf{A}$ and its inverse, denoted by $\mathbf{A}_\mathrm{inv}$ symbol, are adapted so that the variances in directions of search process is increased or decreased.

If evaluation process is succeeded, a positive update for $\mathbf{A}$ and $\mathbf{A}_\mathrm{inv}$ is used. In this condition, the updating process is performed on a search (evolution) path $\mathbf{p}_\mathbf{A}$, where $\mathbf{p}_\mathbf{A} \in \mathbb{R}^n$, for direction of search process that accumulates successful mutation vector with old information of evolution path.

$$\mathbf{p}_\mathbf{A}^{(g)} = (1-c)\mathbf{p}_\mathbf{A}^{(g-1)} + \sqrt{c(2-c)}\mathbf{A}^{(g)}\mathbf{z}^{(g)} \tag{37}$$

where c is a learning rate as an exogenous parameter that equal to $2/(n+2)$.

Contrary, in the case of unsuccessful evaluation, the Cholesky factor and its inverse are updated so that reducing the variances of the mutation vector in directions of search process. This negative update occurred when the objective function value at each generation is worse than the value of its k'-th predecessor that is so-called especially unsuccessful. Throughout this paper, k' is considered equal to five. The update equations of matrices $\mathbf{A}$ and $\mathbf{A}_\mathrm{inv}$ can be defined by

$$\mathbf{A}^{(g+1)} = a\mathbf{A}^{(g)} + b\left(\mathbf{A}^{(g)}\mathbf{w}^{(g)}\right)\left(\mathbf{w}^{(g)}\right)^\mathrm{T} \tag{38}$$

$$\mathbf{A}_{\text{inv}}^{(g+1)} = \frac{1}{a}\mathbf{A}_{\text{inv}}^{(g)} - \frac{b\mathbf{w}^{(g)}}{a^2 + ab\|\mathbf{w}^{(g)}\|^2}\left(\left(\mathbf{w}^{(g)}\right)^{\mathrm{T}}\mathbf{A}_{\text{inv}}^{(g)}\right) \tag{39}$$

that

$$\mathbf{w}^{(g)} := \begin{cases} \mathbf{A}_{\text{inv}}^{(g)}\mathbf{p}_{\mathrm{A}}^{(g)}, & \text{if evaluation succeeded} \\ \mathbf{z}^{(g)}, & \text{otherwise} \end{cases}$$

$$a := \begin{cases} \sqrt{1 - c_{\text{cov}}}, & \text{if evaluation succeeded} \\ \sqrt{1 + c'_{\text{cov}}}, & \text{otherwise} \end{cases}$$

$$b := \begin{cases} \dfrac{a}{\|\mathbf{w}^{(g)}\|^2}\left(\sqrt{1 + c_{\text{cov}}a^{-2}\|\mathbf{w}^{(g)}\|^2} - 1\right), & \text{if succeeded} \\ \dfrac{a}{\|\mathbf{w}^{(g)}\|^2}\left(\sqrt{1 - c'_{\text{cov}}a^{-2}\|\mathbf{w}^{(g)}\|^2} - 1\right), & \text{otherwise} \end{cases}$$

where c_{cov} and c'_{cov} are a learning rate for positive and negative update of the Cholesky factor, respectively. These parameters are defined as

$$c_{\text{cov}} = 2/(n^2 + 6) \tag{40}$$

$$c'_{\text{cov}} = \min\left(\frac{0.4}{n^{1.6} + 1}, \frac{1}{2\|\mathbf{z}^{(g)}\|^2 - 1}\right) \tag{41}$$

Finally, note here the evolution path $\mathbf{p}_{\mathrm{A}}^{(0)}$ is generally initialized to be zero.

Updating mutation strength: The process of updating causes to improve in finding near-optimal solution, significantly. To control the mutation strength a scalar-valued success rate is utilized. This parameter is adapted based on the evaluation result as

$$p_{\sigma}^{(g)} := \begin{cases} \left(1 - c_p\right)p_{\sigma}^{(g-1)} + c_p, & \text{if evaluation succeeded} \\ \left(1 - c_p\right)p_{\sigma}^{(g-1)}, & \text{otherwise} \end{cases} \tag{42}$$

where c_p is a learning rate $\left(0 < c_p \leq 1\right)$ and is equal to $1/12$. Therefore, the mutation strength is updated by

$$\sigma^{(g+1)} = \sigma^{(g)}.\exp\left(\frac{p_{\sigma}^{(g)} - p_{\mathrm{t}}}{d_{\sigma}(1 - p_{\mathrm{t}})}\right) \tag{43}$$

where $d_{\sigma} = (1 + n/2)$ is a damping factor and p_{t} denotes target success rate and is equal to $2/11$. The success rate $p_{\sigma}^{(0)}$ is initialized to p_{t}. In each generation, the mutation strength becomes smaller and, thereby, the ES approaches the optimum.

B. *ES Optimization Process*

Briefly, the evolution strategies fulfil by an iterative procedure that way at every iteration (generation), the current (parent) solution is mutated and one offspring is procreated. Then, their objective function value (fitness) is evaluated. According to the evaluation result, the mutation strength, the Cholesky factor, and its inverse are updated based on some exogenous and adapted endogenous parameters where they lead to improve the mutation distribution in next generation. This procedure is iterated until the objective is fully optimized without stagnation of the search process.

VI. Case Study

A. *Simulation Model*

As a case study, a series-parallel HEV that in this work denoted by SPHEV, was equipped with a simple planetary gear train that physically connected same as the THS connections was modeled. The power flow of the series-parallel structure was discussed in [6] and [13]. Table I shows the parameters of the studied HEV system. The objective of this case study is improving control operations by realization of the LS and ES techniques on the SPHEV under several prescribed driving cycles. The optimization process is run on Matlab platform with Core i5-4460 processor and 8GB DDR3 RAM.

With considering the computational time and ensuring the precision, the time interval (Δt) for sampling is set as one second. In this paper, all the presented simulations have been done on the WLTP (class 3), FTP, JC08 and NEDC.

Regarding to the proposed simplified model template in section II, a complete HEV model for this structure was designed. Moreover, the below assumptions were considered.

- The efficiency of the power splitter and mechanical transmission are assumed to one.
- The electric auxiliary loads in the vehicle are negotiated.
- The temperature effects on the battery are negotiated.
- Due to the difference between the mass of the vehicle and the inertia of the engine, the inertia effects of the engine during starting and stopping are negotiated.

Finally, in the discrete-time format, the mathematical model of this HEV with considering three state variables (the SoC level, the engine speed, and the vehicle speed) adequately can be summarized in (44) to (46).

The optimization objective is to choose, at each sampling time, the optimal or near-optimal engine torque (T_{e}) and EM2 torque (T_{em2}) variables as vector-valued decision variables $\mathbf{u}$ on search space $\mathcal{U}$ according to the minimization of the total fuel consumption over the speed cycle. It means that the optimization objective in this case study is to control the engine and EM2 torques such that the fuel consumption is reduced, while the drivability remains unaffected. Therefore, the responsibility of the engine operating points is on the optimizer. In this case, the search vector and decision vector are the same. The equality constraints are constructed by the mathematical relations between main propulsive components of the SPHEV system regarding to the proposed model in section II. The inequality constraints consist of some local constraints and a global constraint. The constraints parameters for the components are summarized in Table I. The local constraints are defined by

- The SoC level should be remained in the pre-set range.
- The operating points of the main propulsive components, i.e. engine, EM1 and EM2, should be in admissible physical boundaries.
- In order to avoiding the fluctuation in the engine operation status, the allowable minimum time for engine in off ($t_{\text{min,off}}$) or on ($t_{\text{min,on}}$) operation are set.
- As the viewpoint of comfortability issues, for avoid volatility on the engine speed when it is running, during sampling moments the engine speed had not been remarkably fluctuated.

The only global constraint of the problem is based on the charge-sustaining issues. To prevent the battery from being drained at the end of driving, the SoC level at the end of driving ($C_{\mathrm{b}}(n)$) should not be lower than the reference value, i.e. initial charge ($C_{\mathrm{b},0}$).

B. Optimization Parameters

The LS & ES Opt. techniques and a baseline rule-based control strategy were applied on SPHEV system with the proposed simplified model of components. Simulation results of the following four control strategies will be analyzed as

- RB_PFCS: Baseline rule-based control strategy where will be discussed in next sub-section.
- LS_SS1: Optimization technique by the first proposed search strategy in LS-framework in section IV.
- LS_SS2: Optimization technique by the second search strategy in LS-framework in section IV.
- ES_ACMA: Optimization technique by the proposed evolution strategy in section V.

For proposed LS strategies, in the case study, the number of the selected search variables (k) in each iteration is four. In addition, the number of adjacent values (l) of each nominated solution was selected as two in this case. Therefore, in each iteration up to 80 feasible neighbor solutions are evaluated. In addition, to implementing the proposed ES technique (ES_ACMA), the initial mutation strength is assumed one.

C. Baseline control strategy

The implemented rule-based control strategy as a baseline to evaluate the results of realized optimization techniques is done by power follower control strategy (PFCS) [14]. Briefly, the state control logic of the engine and battery in the PFCS is summarized in Table II.

D. Results

In this work, the results of applied optimization techniques can serve a bound of energy management in an HEV for several driving cycles with considering before mentioned constraints. However, practical implementation of optimal or near-optimal control strategies in HEVs needs to be traded off with other vehicle issues such as emissions to make tradeoffs. In the Table III, the fuel consumption of four control strategies are shown. The minimal performance indices belong to running optimization processes on JC08 cycle by up to 7% reduction proportion to PFCS in LS-SS2 search strategy. Decreasing fuel consumption on highway driving section causes to improve fuel economy for LS-SS2. In this research, Figs. 13 to 19 show the JC08 simulation results. The performance index of LS-SS2 is the lowest among other control strategies in JC08 simulation.

Figs. 13 and 14 show the engine and the EM2 torque's changes during JC08 driving mission. With considering the engine torque characteristics, as can be seen in Fig. 13, the engine torque in city driving section often operates in lower values than the maximum level.

The Figs. 15 and 16 show the state's characteristics of HEV-system. In the Fig. 15, the smoothness behavior in the engine speed is obvious due to drivability and comfortability constraints. The both of LS search strategies have maximum speed during highway driving. However, since the fuel consumption is related to the engine speed, the LS-SS2 shifted the engine operating points on the lower speeds.
In the Fig. 16, the SoC of all control strategies have similar pattern, especially, the PFCS pattern is significantly higher than the other patterns in second half of JC08. The final SoC of all control strategies is close to the reference SoC.

The Fig. 17 shows the pattern of finding near-optimal solutions during optimization process. The ES_ACMA evaluated more than 4.5e5 while for the LS_SS2 is around 10000. As the viewpoint of computational time, Table IV shows the computational time of realized control

TABLE I. COMPONENT DATA FOR THE SERIES-PARALLEL HEV.

Electric machine (EM1)	Type: PMSM motor/inverter; Maximum power: 60 [kW] corresponding to maximum velocity 10000 [rpm].
Electric traction machine (EM2)	Type: PMSM motor/inverter; Maximum power: 50 [kW] @ 1200-6000 [rpm]; Max. torque: 400 [Nm] @ 0-1200 [rpm];
Mechanical transmission	The transmission ratios are unity and equal to 4.113 [-]
Battery pack	201.6 [V] Ni-MH; Capacity: 6.5 [Ah]; Internal resistance = 0.37 [Ω]; Max. discharging power: 21[kW]; Max. charging power: 25 [kW]; SoC range: 40-80 [%]; Initial SoC: 60%
Engine data	SI Atkinson ICE; Size: 1.5 [L]; Max. power: 57 [kW] @ 5000 [rpm], Max. torque: 115 [Nm] @ 4200 [rpm]; Idle speed: 1200 [rpm] by torque 90 [Nm]; Inertia: 0.13 [kg.m^2]; Init. velocity: 0; $t_{\mathrm{min,off}}$: 10 [s]; $t_{\mathrm{min,on}}$: 18 [s]
Power splitter	The proportion of the gears teeth: $c_{\mathrm{P2}}/c_{\mathrm{P1}} = 2.6$;
Vehicle body & wheel	Mass: 1460 [kg]; Air drag coefficient: 0.33 [-]; Frontal area: 3.8 [m^2]; Roll resistance coefficient: 0.015 [%]; Maximum regenerative brake fraction: 0.4 [-]; Wheel radius: 0.3 [m]

$$\Delta V + \left(\frac{J_{\mathrm{e}} c_{\mathrm{T1}} c_{\mathrm{P2}}}{r_{\mathrm{w}} m_{\mathrm{V}} (c_{\mathrm{P1}} + c_{\mathrm{P2}})}\right) \Delta\omega_{\mathrm{e}} = \left(\frac{-\rho A c_{\mathrm{d}}}{2 m_{\mathrm{V}}}\right) V^2 + \left(\frac{c_{\mathrm{T1}} c_{\mathrm{P2}}}{r_{\mathrm{w}} m_{\mathrm{V}} (c_{\mathrm{P1}} + c_{\mathrm{P2}})}\right) T_{\mathrm{e}} + \left(\frac{c_{\mathrm{T2}}}{r_{\mathrm{w}} m_{\mathrm{V}}}\right) T_{\mathrm{em2}} - \left(g_{\mathrm{e}} c_{\mathrm{r}} + \frac{T_{\mathrm{br}}}{r_{\mathrm{w}} m_{\mathrm{V}}}\right) \tag{44}$$

$$J_{\mathrm{e}} \Delta\omega_{\mathrm{e}} = T_{\mathrm{e}} - \left(\frac{c_{\mathrm{P1}} + c_{\mathrm{P2}}}{c_{\mathrm{P1}}}\right) T_{\mathrm{em1}} \tag{45}$$

$$\Delta C_{\mathrm{b}} = -\frac{U_{\mathrm{oc}}(C_{\mathrm{b}}) - \sqrt{U_{\mathrm{oc}}^2(C_{\mathrm{b}}) - 4\left(P_{\mathrm{em2,e}} - P_{\mathrm{em1,e}}\right) \times R_{\mathrm{b}}}}{2 Q_{\mathrm{b}} R_{\mathrm{b}}} \tag{46}$$

$$P_{\mathrm{em1,e}} = \frac{T_{\mathrm{em1}}}{K_{\mathrm{em1}}}\left(K_{\mathrm{em1}} \omega_{\mathrm{em1}} - \frac{R_{\mathrm{em1}}}{K_{\mathrm{em1}}} T_{\mathrm{em1}}\right), \qquad P_{\mathrm{em2,e}} = \frac{T_{\mathrm{em2}}}{K_{\mathrm{em2}}}\left(K_{\mathrm{em2}} \omega_{\mathrm{em2}} + \frac{R_{\mathrm{em2}}}{K_{\mathrm{em2}}} T_{\mathrm{em2}}\right)$$

$$\omega_{\mathrm{em1}} = \left(\frac{c_{\mathrm{P1}} + c_{\mathrm{P2}}}{c_{\mathrm{P1}}}\right) \omega_{\mathrm{e}} - \left(\frac{c_{\mathrm{P2}}}{c_{\mathrm{P1}}}\right) \omega_{\mathrm{em2}}, \qquad \omega_{\mathrm{em2}} = \left(\frac{c_{\mathrm{T2}}}{r_{\mathrm{w}}}\right) V$$

TABLE II. THE STATE CONTROL LOGIC OF THE ENGINE AND BATTERY IN THE RULE-BASED PFCS.

Rule-Based condition	Driving functionality conditions	Commands
$(0 \le P_{tc} \le \overline{P}_{b,dis}) \cap (\underline{C}_b \le C_b \le \overline{C}_b)$	$P_b(t) = P_{tc}(t)$	$S_e(t) = 0$
$(0 \le P_{tc} \le \overline{P}_{b,dis}) \cap (C_b < \underline{C}_b)$	$P_b(t) = \{P_{tc}(t) - P_e(t) \mid P_{tc}(t) < P_e(t)\}$	$S_e(t) = 1$
$(0 \le \overline{P}_{b,dis} \le P_{tc}) \cap (C_b < \underline{C}_b)$	$P_b(t) = \{P_{tc}(t) - P_e(t) \mid P_{tc}(t) < P_e(t)\}$	$S_e(t) = 1$
$(0 \le \overline{P}_{b,dis} \le P_{tc}) \cap (\underline{C}_b \le C_b \le \overline{C}_b)$	$P_b(t) = P_{tc}(t) - P_e(t)$	$S_e(t) = 1$
$(0 \le \overline{P}_{b,dis} \le P_{tc}) \cap (C_b > \overline{C}_b)$	$P_b(t) = \{P_{tc}(t) - P_e(t) \mid P_{tc}(t) > P_e(t)\}$	$S_e(t) = 1$
$(\overline{P}_{b,ch} \le P_{tc} \le 0) \cap (\underline{C}_b \le C_b \le \overline{C}_b)$	$P_b(t) = P_{tc}(t)$	$S_e(t) = 0$

P_{tc}: the required/supplied power at the vehicle shaft
S_e: the engine operation status
P_e: the output power of the engine
P_b: the output power of the battery
$\overline{P}_{b,dis}$: the maximum discharge power of the battery
$\overline{P}_{b,ch}$: the maximum charge power of the battery

strategies. The search process by LS-SS2 is the fastest among the proposed search strategies.

In the case of the behavior of the strategies in typical one time run on the discus function, the time consuming for each iteration with considering the neighborhood function for the LS search strategies are around 9 seconds, whereas, for the ES_ACMA is around 1 second.

Figs. 18 and 19 show the total computational time during running optimization process. The highest succeed evaluation is belonged to ES_ACMA by around 270, as can been seen in Fig. 19. The highest rate for finding near-optimal solutions and total number of successful evaluations is belonged to ES_ACMA control strategy. The LS_SS2 could find the improved solution close to the other strategies in lowest computational time.

VII. CONCLUSION

In this paper, the control operations, which implemented by heuristic methods, were optimized by two metaheuristics optimization techniques in the EM problem under a-priori knowledge driving missions where can lead to derive the efficient EM strategies.

At the first, a general method for modeling HEV-system was proposed. The simplicity, generality, and flexibility of the computational model in the EM problems are impact factors. To reduce the scale of the model, the energy converters were modeled as an energy transform gain where no map for the coefficients was not required. The model structure is transparent and evaluation of parameters and simulation are easy. Therefore, the EM problem can be numerically setup easily for any kind of HEV structure.

The effective control strategies to improve the EM system as the viewpoint of fuel reduction was proposed. The local search and evolutionary strategy optimization techniques were newly implemented by an approach for realizing in the EM problem of HEV-system for finding the time-series of optimal or near-optimal sequences of decision variables. To our knowledge, no previous research has been studied on the realizing these control strategies on the EM problem.

A computational experiment set on the series-parallel HEV

TABLE III. INCREMENT FUEL CONSUMPTION FOR CONTROL STRATEGIES.

CS \ Cycle	WLTP_C3	FTP	JC08	NEDC
PFCS	1062.7	745.99	320.28	520.9
LS_SS1	1029	715.033	302.236	516.755
LS_SS2	1031.7	717.0216	298.219	518.72
ES_ACMA	1037	738.153	301.878	506.0704

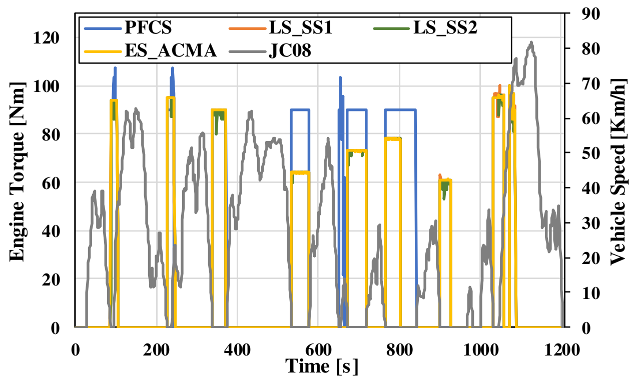

Fig. 13. The engine torque characteristic as the decision variable on JC08

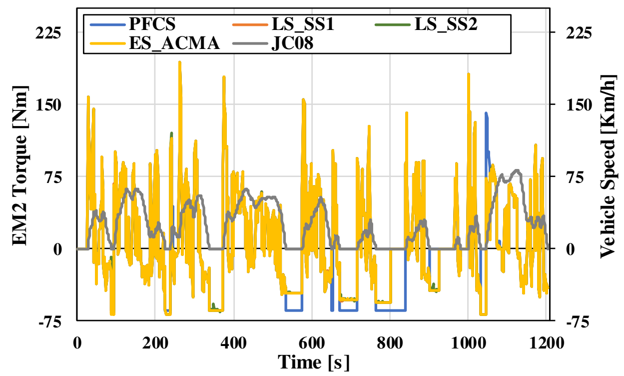

Fig. 14. The EM2 torque characteristic as the decision variable on JC08

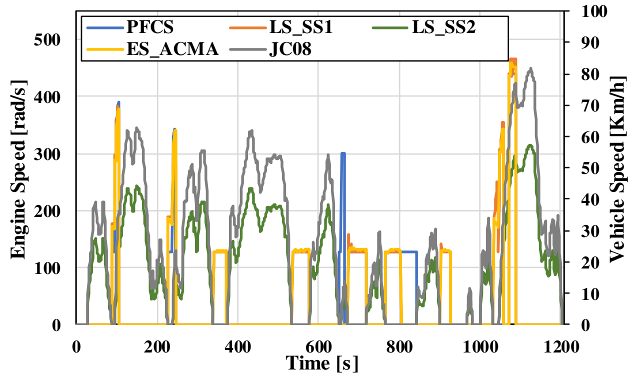

Fig. 15. The engine speed characteristics as the state variable on JC08

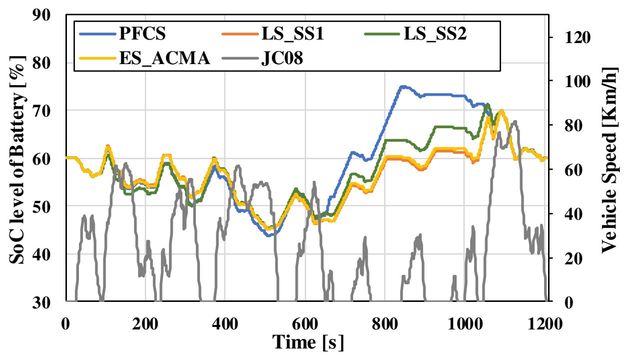

Fig. 16. The battery SoC level characteristics as the state variable on JC08

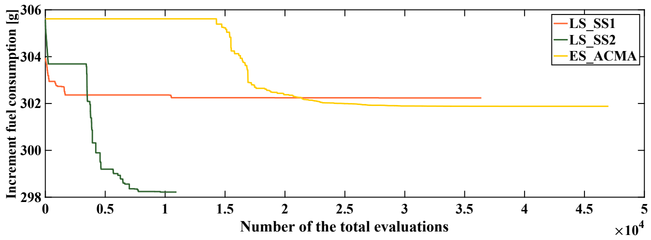

Fig. 17. The pattern of finding near-optimal solution during optimization process on JC08

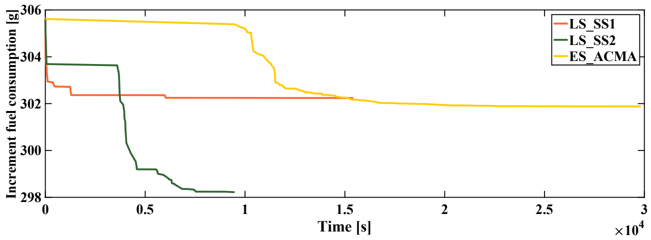

Fig. 18. The total computational time during running optimization process vs. obtained near-optimal solutions on JC08

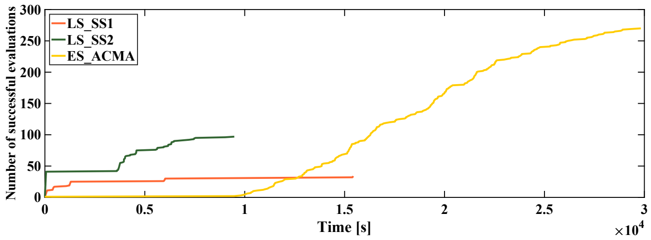

Fig. 19. The total computational time during running optimization process vs. the total number of obtained near-optimal solutions on JC08

TABLE IV. COMPUTATIONAL TIME OF OBTAINING NEAR-OPTIMAL SOLUTIONS ON JC08

Control strategies	RB_PFCS	LS_SS1	LS_SS2	ES_ACMA
Optimization time	---	4.27 [h]	2.63 [h]	8.28 [h]

as a case study was used in this paper and shows the energy management concept was working which revealed improved control operations as the viewpoint of fuel economy.

Through the results of computational experiments, the control strategies by the proposed methodologies cause to obtaining near-optimal solutions in the EM problem on prescribed driving cycle, which are usable to derive rule for the EM controller. Thereby, a fuel reduction of around 7% could be obtained and could be calculated with sufficient accuracy in comparison with the rule-based PFCS. The computational cost of running the optimization procedure is enhanced. Obviously, the proposed methods can be applied to other HEV configurations. Thus, the authors have concluded the proposed methods were suitable for the proposed approach which causes to improve the existing EM control logic and therefore, leads to design efficient EM controller with good balance of optimality and practicability.

To achieving the final goal of this research, the obtained improved solutions by the proposed methods will be applied by machine learning techniques, in the next research step. In addition, continuing this approach the study on the EM problem with the prediction of future driving situations will be explored in the future.

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