Design and Optimization of Hybrid Electric Vehicle Drivetrain and Control Strategy Parameters Using Evolutionary Algorithms

Chirag Desai

A Thesis

in

The Department

of

Electrical and Computer Engineering

Presented in Partial Fulfillment of the Requirements for the

Degree of Master of Applied Science (Electrical Engineering and Computer Science) at

Concordia University

Montréal, Québec, Canada

December 2010

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Chirag Desai

Entitled: "Design and Optimization of Hybrid Electric Vehicle Drivetrain and Control Strategy Parameters using Evolutionary Algorithms

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science

Complies with the regulations of this University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

____ Chair
Dr. D. Qiu

____ Examiner, External
Dr. S. Rakheja, MIE To the Program

____ Examiner
Dr. P. Pillay

____ Supervisor
Dr. S. Williamson

Approved by: ____
Dr. W. E. Lynch, Chair
Department of Electrical and Computer Engineering

__________20_____ ________________________________
Dr. Robin A. L. Drew
Dean, Faculty of Engineering and Computer Science

ABSTRACT

Design and Optimization of Hybrid Electric Vehicle Drivetrain and Control Strategy Parameters Using Evolutionary Algorithms

Chirag Desai

Advanced propulsion technologies such as hybrid electric vehicles (HEVs) have demonstrated improved fuel economy with lower emissions compared to conventional vehicles. Superior HEV performance in terms of higher fuel economy and lower emissions, with satisfaction of driving performance, necessitates a careful balance of drivetrain component design as well as control strategy parameter monitoring and tuning. In this thesis, an evolutionary global optimization-based derivative-free, multi-objective genetic algorithm (MOGA) is proposed, to optimize the component sizing of a NOVA® parallel hybrid electric transit bus drivetrain. In addition, the proposed technique has been extended to the design of an optimal supervisory control strategy for effective on-board energy management. The proposed technique helps find practical trade off-solutions for the objectives. Simulation test results depict the tremendous potential of the proposed optimization technique in terms of improved fuel economy and lower emissions (nitrous-oxide, NOx, carbon monoxide, CO, and hydrocarbons, HC). The tests were conducted under varying drive cycles and control strategies.

ACKNOWLEDGMENTS

The author would like to express his most sincere gratitude to his supervisor, Dr. Sheldon S. Williamson, for his patient and invaluable guidance, advice, and friendship throughout the Master's program. Also, the author deeply appreciates the financial support from his supervisor.

The author would like to thank his other distinguished professors and colleagues in the Power Electronics and Energy Research (PEER) group, within the P. D. Ziogas Power Electronics Laboratory. The precious assistance from Mr. Manu Jain is much appreciated. The author would like to extend a special vote of gratitude towards Prof. Pragasen Pillay, for his valuable suggestions and comments. In addition, the author would like to thank Prof. Luiz Lopes and Mr. Joseph Woods for their constant assistance and support.

Last, but not least, the author would like to extend his sincere gratitude to his close relative and friends for their steady support and encouragement.

Author would like to dedicate this work to his

Mother, Mrs. Rekha Desai, Father, Mr. Dililpkumar Desai, Brother, Nirav Desai,

and his would-be Wife, Ms. Jolly Sandhu.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ADVISOR	Advanced Vehicle Simulator
AER	All Electric Range
Ah	Ampere-Hour
CD	Charge Depleting
CO	Carbon Monoxide
CS	Control Strategy
CV	Conventional Vehicle
DP	Dynamic Programming
EA	Evolutionary Algorithm
ECMS	Equivalent Consumption Minimization Scheme
EM	Electric Motor
EUDC	Extra-Urban Drive Cycle
ESS	Energy Storage System
EV	Electric Vehicle
g/km	Grams per kilometer
GA	Genetic Algorithm
GPS	Global Positioning System
HC	Hydrocarbons
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
km/h	Kilometers per hour

LP	Linear Programming
MOEA	Multi-Objective Evolutionary Algorithm
MOGA	Multi-Objective Genetic Algorithm
L/100	Liters per gallon
NiMH	Nickel Metal Hydride
NO_X	Nitrous Oxide
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PHEV	Plug-in Hybrid Electric Vehicle
PAES	Pareto Archived Evolutionary Strategy
RB	Rule-Based
SOC	State of Charge
SOOP	Single Objective Optimization Problem
SPEA	Strength Pareto Evolutionary Algorithm
SQP	Sequential Quadratic Programming
UC	Ultra-capacitor
UDDS	Urban Dynamometer Driving Schedule
ZEV	Zero Emission Vehicle

LIST OF PRINCIPAL SYMBOLS

cs_charge_trq	Additional torque required from engine to charge or discharge the battery based on battery SOC
cs_electric_speed_lo	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at low battery SOC
cs_electric_speed_hi	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at high battery SOC
cs_lo_soc	Lowest desired battery state of charge
cs_hi_soc	Highest desired battery state of charge
cs_min_trq_frac	Fraction of ICE maximum torque at each speed above which ICE must operate if SOC < (cs_lo_soc)
cs_off_trq_frac	Fraction of ICE maximum torque at each speed at which the ICE should turn off when SOC > (cs_lo_soc)
ess_cap_scale	ESS capacity scale factor
di	Crowding distance of point i
fc_trq_scale	ICE torque scale factor
η	Efficiency
J	Cost function
mc_trq_scale	EM torque scale factor
P_0	Parent Population
P_{EM}	Electric motor power
P_{LOAD}	Load power
P_{ICE}	ICE power

Q_0	Offspring Populations
R_t	New population
$\tau_{additional}$	Additional torque
τ_{charge}	Charge torque
$\tau_{ICE\ off}$	Engine off torque
$\tau_{off\ frac.}$	Off torque fraction
τ_{max}	Maximum engine torque
$\tau_{min.efficiency}$	Minimum efficiency torque
W_i	Weights

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The growing need to reduce fuel consumption and emissions in the transportation sector has inspired urban transit fleet operators to pioneer the adoption of advanced electric drive system technologies. Hybrid electric drive systems for transit bus applications are being aggressively investigated as a means of improving fuel economy, reducing emissions, and lowering operation and maintenance costs [1]. A hybrid electric vehicle (HEV) improves overall drive system efficiency, reduces fuel consumption and emissions, recovers braking energy, and improves driveability [2]. Conventional transit buses exhibit relatively poor fuel economy and moderately high emissions while pure battery electric transit buses cannot meet demands of most transit duty cycles. Moreover, all electric range of EVs is limited, due to battery limitations. In addition fuel cell and plug-in hybrid electric transit buses are still in their development stages and are not yet cost-effective. However, hybrid electric drivetrains that use two or more sources of on-board energy can easily satisfy urban transit bus drive cycle requirements, while dramatically improving fuel economy and emissions. Thus, hybrid electric propulsion has emerged as an efficient solution for transit vehicles as well as other light and heavy-duty vehicles.

1.1.1 WORKING PRINCIPLE OF AN HEV DRIVETRAIN

Typically HEVs have an electric drivetrain equipped with a bidirectional energy storage device. Traditional internal combustion engine (ICE) is used as a unidirectional energy source. Using an electro-chemical battery is the most common practice as an HEV energy storage device. An ultracapacitor and/or flywheel can also be integrated with batteries as a secondary energy source. Fig. 1-1 illustrates the general concept and power flow of a typical HEV. In order to satisfy load requirements, the HEV can select any power flow path. Moreover, in an HEV drivetrain, vehicle braking energy can be recuperated efficiently. The control strategy of an HEV can be designed for various purposes, based on the different combinations of power flows.

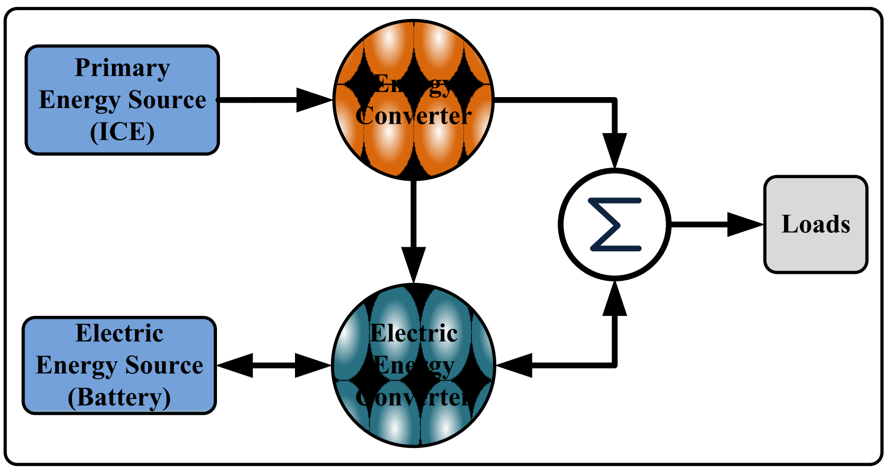


Fig. 1-1 Illustration of power flow within the hybrid electric vehicle drivetrain

As illustrated in the Fig. 1-1, considering the drivetrain is a combination of fuel energy and electric energy, the HEV can work in the following modes [3]:

- ICE solely drives the load;
- Electric Motor (EM) solely drives the load;
- Both ICE and EM drive the load at the same time;
- ICE charges the Energy Storage System (ESS) and the EM propels the vehicle (series HEV);
- ESS is being charged from load during regenerative braking;

- ICE charges ESS;
- ESS is charged by ICE as well as regenerative braking;
- Finally, ICE delivers power to drive the vehicle as well as to charge the ESS.

This liberty to select various power flow combinations creates tremendous flexibility of operation compared to conventional vehicles (CVs). However, such an operational characteristic introduces an interesting series of performance issues, which necessitates careful design of drivetrain components and control strategy parameters.

1.2 BASIC HEV DRIVETRAIN CONFIGURATIONS

As discussed in the previous section, propulsion energy of an HEV comes generally from two types of sources; one of them must be an electric source. In addition, integrating an EM with an ICE is the most practical means of realizing an HEV arrangment, before the pure electric vehicle (EV) eventually becomes commercial. Based on different combinations of electric and mechanical traction, HEV drivetrains are divided into three basic arrangements: series, parallel, and series-parallel combined hybrids, as shown in Fig.1-2, Fig.1-3, and Fig.1-4, respectively [4].

1.2.1 SERIES HYBRID ELECTRIC VEHICLE

A series HEV typically consists of an internal combustion engine (ICE) directly coupled to an electric generator. The electric motor provides all the propulsion power. The electric generator is connected to the DC power bus via a controlled power electronic converter. An energy storage system (ESS) is connected to the DC power bus through a bidirectional controlled DC/DC converter. The traction motor is connected to the DC power bus by means of a motor controller, which is a bidirectional controlled DC/AC inverter. The configuration of a series HEV is shown in Fig. 1-2. The vehicle master controller manages power flow based on power demand and power requirement from other components.

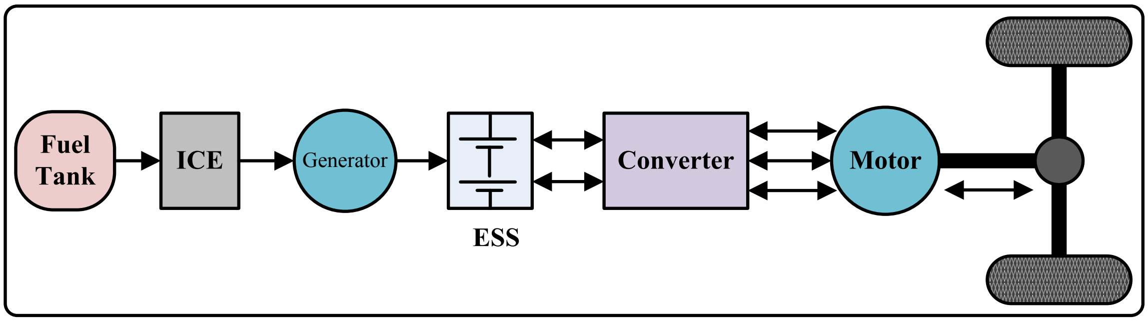


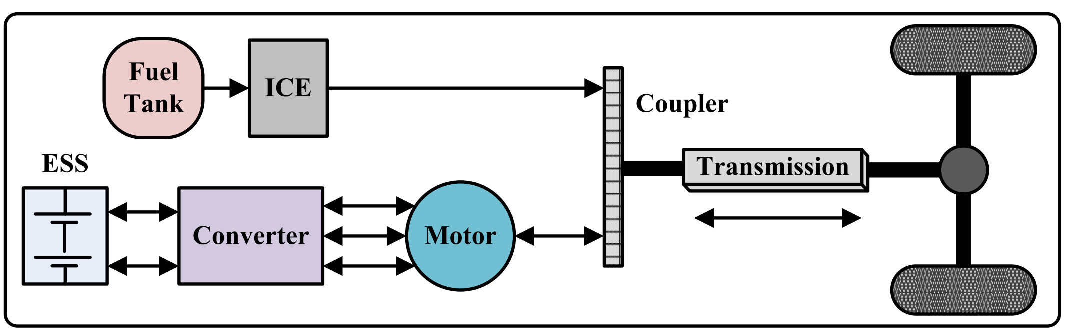
Fig. 1-2 Series HEV drivetrain configuration

In a series HEV, because of no mechanical connection between the ICE and drive wheels, it is possible to operate the ICE very close to maximum effieciency. The ICE works in its optimal operation range as an on-board generator, maintaining battery state of charge (SOC) [5]. Thus, the control of a series HEV is fairly straightforward, compared to other HEV drivetrains.

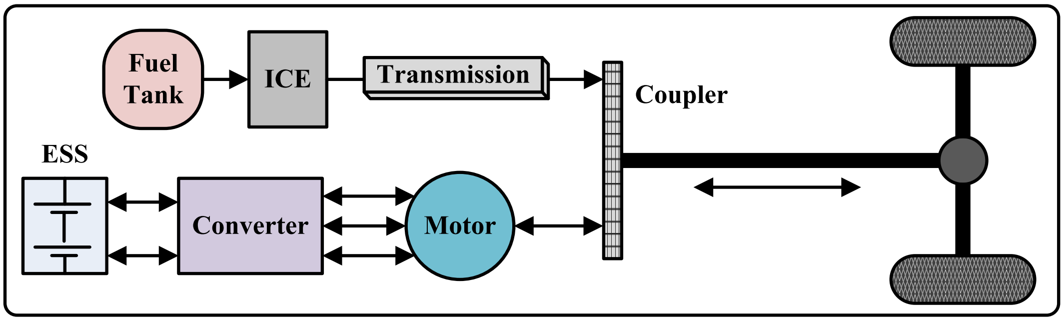
At the same time, multiple energy conversion stages exist in a series HEV. Mechanical energy of the ICE is converted into electrical energy via the generator. At the same time, electrical energy is converted into mechanical energy via the electric motor. Thus, the inefficiencies of the generator and traction motor may cause significant losses. The electric generator adds additional cost and weight. Because the electric motor provides the sole propelling power to the vehicle, in order to satisfy vehicle performance, in terms of acceleration and gradeability, the electric motor and the ESS must be properly sized.

1.2.2 PARALLEL HYBRID ELECTRIC VEHICLE

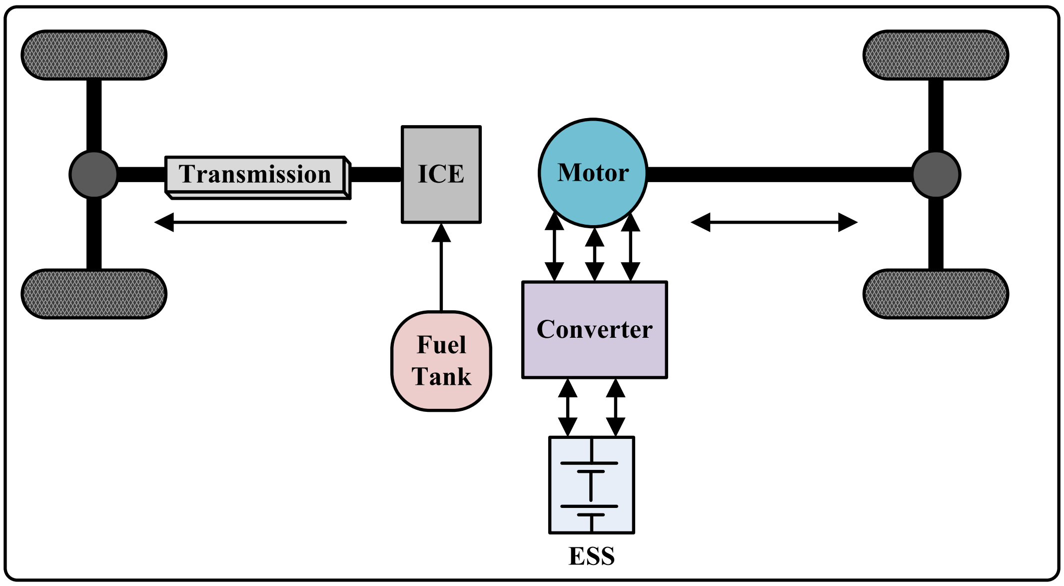
In a parallel HEV, both the ICE and the electric motor deliver power to the wheels. A parallel HEV configuration offers freedom to choose a combination of traction sources. By merging the two different traction sources, a relatively smaller, more efficient ICE can be used. In addition, a parallel HEV arrangement requires a relatively smaller battery capacity compared to a series HEV, which reduces dirvetrain mass. In parallel HEVs, the ICE is not directly connected to the generator, as in series HEVs. Instead, the ICE is directly coupled to the transmission. Output torques of the ICE and the EM are mechenically coupled through a torque coupler. The coupling device could be a chain drive, a belt drive, or a gearbox. Depending on the position of coupling device, a parallel HEV can be further subcategorized as pre-transmission or post-transmission parallel HEV [6]. Figs. 1-3 (a) and 1-3 (b) illustrate the configuration of pre-transmission and post-transmission parallel HEV, respectively. Occassionally,in parallel HEVs, the ICE and the EM drive separate sets of wheels. Hence, the two torques are coupled through the road. This type of parallel HEV provides all-wheel drive capability. Fig. 1-3 (c) shows parallel through-the- road HEV configuration.



(a) Pre-transmission parallel HEV



(b) Post-transmission parallel HEV



(c) Through-the-road parallel HEV

Fig. 1-3 Parallel HEV drivetrain configurations

In a parallel HEV drivetrain, both the engine and the electric motor directly supply torques to the driven wheels, and no energy conversion occurs. Thus, the energy loss is low, which increases overall drivetrain efficiency. Moreover, the parallel HEV drivetrain is compact, due to the absence of an electric generator. The small size of ESS and EM also makes the parallel HEV an attractive options. However, the control of parallel HEV drivetrain is more complicated than a series HEV.

1.2.3 SERIES-PARALLEL HYBRID ELECTRIC VEHICLE

By adding a power split unit between the generator, the electric motor, and the engine, the series-parallel hybrid HEV combines the features of a series HEV as well as a parallel HEV, as shown in Fig. 1-4. Although it has the advantages of both series and parallel configurations, it also has the drawbacks of these two configurations. In addition, the technical complexity of the general design and development of the combined HEV drivetrain and its precise control strategy is a major challenge.

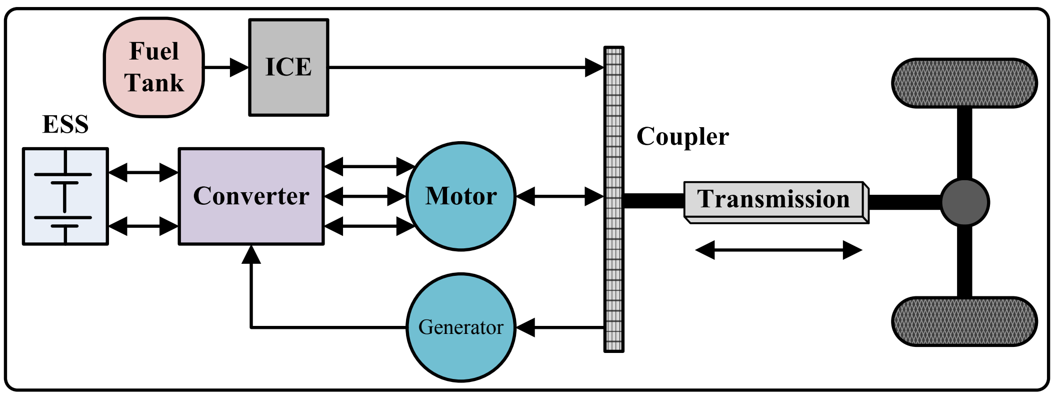


Fig. 1-4 Series-parallel HEV drivetrain configuration

1.3 CONTRIBUTION OF THE THESIS

The major contributions of this Thesis include:

(a) Define and recognize the problem of HEV drivetrain component sizing and control strategy parameter optimization.

(b) Review and classification of HEV control strategies. A detailed overview of different existing control strategies, along with their respective merits and demerits. The overall effect of different control strategies (CS) on HEV drivetrain efficiency and the compatibility of optimal CS options for parallel HEV drive.

(c) Implementation of multi-objective non-dominated sorting genetic algorithm II (NSGA-II) for the parameter optimization of NOVA parallel hybrid electric transit bus.

(d) Analysis and validation of obtained trade-off solutions.

(e) Introduce a possible future plug-in version of NOVA parallel hybrid transit bus, along with a modified structure of a PHEV drivetrain.

(f) Introduce hybrid vehicle control strategy design using model based graphical technique.

1.4 THESIS OUTLINE

The contents of this thesis are organized into 7 chapters. This chapter (Chapter 1) provided a brief introduction to the project as well as the general concepts and configurations of HEVs. It also summarizes the major contribution of the Thesis.

Chapter 2 presents the HEV optimization problem and issues of classic optimization techniques to solve HEV parameter optimization. In this chapter, a population based evolutionary optimization alogorithm is discussed as an alternative to solve HEV parameter optimization.

Chapter 3 reviews and categorizes HEV control strategies (CS). This chapter provides a detailed overview of different existing CS along with their respective merits and demerits. This chapter gives insights into the overall effect of different CS on HEV drivetrain efficiency and the compatibility of optimal CS options for parallel HEV drivetrains.

Chapter 4 presents the basics and applications of multi-objective genetic algorithm in NOVA parallel HEV transit bus design problem. In this chapter, the parameter optimization of NOVA parallel hybrid electric transit bus is carried out using NSGA-II optimization algorithm. The algorithm considers fuel economy as well as emissions as design objectives, drivetrain component and control strategy parameters as design variables, and vehicle acceleration and gradeability performance criterions as constraints. The modeling and simulation test results for the NOVA parallel hybrid transit bus parameters are analyzed after optimization, which shows substantial improvements in vehicle performance in terms of improved fuel economy and reduced emissions.

Chapter 5 presents a possible future plug-in HEV version of a NOVA transit bus. This chapter also proposes a modified structure of a PHEV drivetrain for a PHEV transit bus. Finally, this chapter describes critical PHEV terminologies as well as defines various control strategies, with their merits and demerits.

Chapter 6 expalins HEV control strategy design using Matlab graphical modelling technique, more commonly known as Stateflow.

Chapter 7 summarizes the research conducted in the Thesis and presents the overall conclusion. Based on the conclusions of this thesis, and recognizing current automotive industry concerns, appropriate future research directions are finally suggested.

CHAPTER 2

HYBRID ELECTRIC VEHICLE OPTIMIZATION PROBLEM

2.1 INTRODUCTION

As was mentioned in the previous chapter, a typical HEV consists of an ICE, an EM, single or multiple energy storage systems (ESS), power electronic converters, and controllers, with intelligent energy management CS. The drivetrain components and the CS have significant effects on fuel economy, emissions, and performance of HEVs [8]. Therefore, design of an efficient HEV requires optimal sizing of its important electrical and mechanical components as well as fine tuning of CS parameters. However, this optimization task becomes more challenging due to the presence of conflicting design objectives, i.e., improvement on one criterion deteriorates others, especially with the existence of large amount of design variables and nonlinear performance constraints. Moreover, the effect of these design parameters on objectives is non-monotonic. The response function may be discontinuous and HEV component models are non-differentiable data maps [9]. Hence, HEV drivetrain parameter optimization can be treated as a multi-objective constrained nonlinear optimization problem.

In this chapter, HEV classic optimization techniques are discussed along with their respective merits and demerits. In addition, a population based multi-objective optimization approach to handle HEV parameter optimization problem is proposed.

2.2 HEV PARAMETER OPTIMIZATION

HEV parameter optimization is multidisciplinary research topic. In the design of an HEV, the preliminary goal is to reduce fuel consumption and emissions, along with the best possible sizing of ICE, EM, and ESS, with tuned CS parameters. Moreover, vehicle performance constraints have to be satisfied. Typical HEV multi-objective problem objectives, design variables, and performance constraints are listed in equations (2-1), (2-2) and (2-3), respectively.

Objectives:

$$\text{Minimize } \left.\begin{aligned} F1(X) &= \{\text{fuel economy}\} \\ F2(X) &= \{\text{emissions}\} \end{aligned}\right\} \tag{2-1}$$

Design Variables:

$$X = \{\text{ICE size, EM size, ESS size, control strategy parameters}\} \tag{2-2}$$

Vehicle Performance Constraints:

Acceleration time and Gradeability (2-3)

Significant portion of recent research work in the field of HEV parameters optimization considers only a singular objective, such as fuel economy or emissions, which are mainly conflicting parameters. Moreover, most conventional optimization methods are deterministic and convert multi-objective optimization problem (MOOP) into a single-objective optimization problem (SOOP), using artificial fix-up approaches. A global optimization approach for simultaneous optimization of HEV parameters has never been discussed in literature. In the following subsection, two most popular classic multi-objective optimization methods are described.

2.2.1 WEIGHTED SUM METHOD

In the weighted sum approach, each objective function is multiplied with a user-supplied weight, and summed together, to form a composite objective function. Optimization of the composite objective function results in an individual objective function optimization that highly depends on selected weights. The weight of an objective is generally chosen in proportion to the objective's relative importance in the problem. For example, in an HEV design problem, the emissions are more important than fuel economy. Thus, the designer can set higher weights for emissions than the fuel economy.

However, it is possible that different objectives have different orders of magnitude. Thus, to set the values of suitable weights and to make objectives equally important, normalization of objectives is required. The weighted sum is the simplest and the most widely used classic optimization method to solve MOOP. For the problem having a convex pareto front, this method guarantees obtaining solutions on the entire pareto front. Nevertheless, in major nonlinear MOOPs, it is difficult to set the weight vectors, to obtain a solution in a desired region of objective space. The method is unable to find optimal solutions for problems with a non-convex pareto-optimal front [10]. For example, if the problem of Fig. 2-1 is considered, the method will only discover the curve "MN" and "PQ." However, the curve "NOP" is not discovered.

2.2.2 ε- CONSTRAINT METHOD

The ε – constraint method considers one objective function as the main objective and the rest as constraints. It then optimizes single-objective problem by restricting each of the constraint functions within pre-specified limits [11]. However in the early HEV development, it is not certain as to which HEV parameter should be treated as the objective and which parameter should be treated as the constraint. Fig. 2-1 shows non-convex pareto front of two objectives problem. If we consider F_2 as an objective and F_1 as a constraint: $F_1(X) < \varepsilon$ .If $\varepsilon_1 = \varepsilon_1^0$, the problem with this constraint divides the original feasible objective space into two portions: $F_1(X) > \varepsilon_1^O$ and $F_1(X) < \varepsilon_1^O$. The left portion becomes the feasible solution of the resulting problem, and the task is to find the solution which minimizes the feasible region. From Fig. 2-1, it is obvious that point 'O' can be found. In this manner, using ε-constraint methods, intermediate pareto-optimal solutions can be found in non-convex objective spaces.

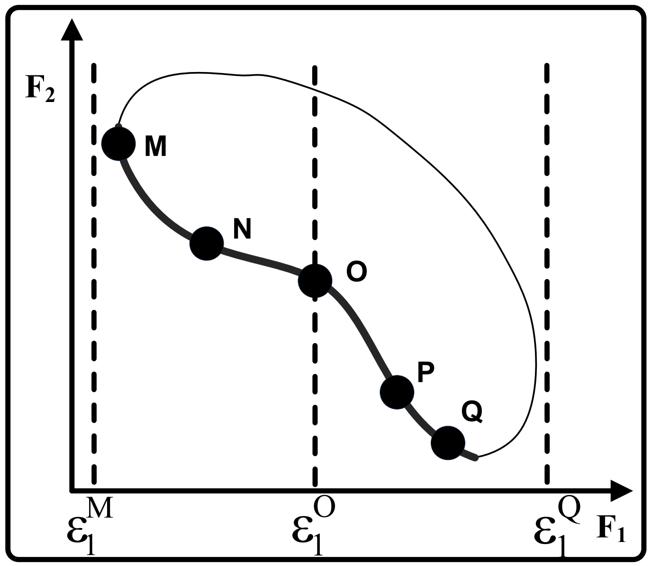


Fig. 2-1 Pareto-optimal front for multi-objective optimization problem

However, in this method, the solutions depend greatly on the values of selected ε constraints. If the values of the constraints are too strict, no feasible solutions may be found. On the other hand, if they are too loose, the requirements may not be fulfilled adequately. Suppose, in Fig. 2-1, ε_1^M is selected, there exists no feasible solution. On the other hand if ε_1^Q is chosen, the entire search space is feasible and the method will always find the optimum 'Q'. In addition, as the number of objectives increases, more information about ε vector is required from the designers.

However, many gradient-based and derivative-free methods of optimization have been proposed to solve this problem. Assanis [12] applied a deterministic sequential quadratic programming (SQP) method, to find optimal drivetrain component sizes. Fish [13] also executed a series HEV sizing by SQP for a specific combat mission. The obtained results proved that SQP converges to local optimum and is not suitable for HEV optimization problem. In reality, SQP relies on the derivative information of the objective function, although the derivative information is not always on hand. For example, the HEV objective functions are discontinuous and discrete. At the same time, HEV component models are non-differentiable. Fellini [14] and Wipke [15] have applied derivative free DIRECT [16] search methods, in HEV optimizations problems to conquer the limitation of gradient-based methods. They concluded that derivative-free methods are more efficient than gradient-based SQP. However, DIRECT optimization methods require a large number of function evaluation and they show slow convergence.

To eliminate these issues related to all classic optimization methods, considerable research has been done in the development of an efficient population based optimization approach of multi-objective evolutionary algorithm (MOEA). Moreover, the concept of dominance aids to resolve some of the issues of classic methods and provides a practical means to handle multiple objectives. An elitist non-dominated sorting genetic algorithm (NSGA-II) has been proven to be an effective tool in solving multi-objective design optimization problems and to find multiple trade-off solutions in a single simulation run. In addition, NSGA-II does not require any artificial fix-ups and information about objective function gradient. Obtained multiple solutions give the designer a comparative scenario to select compromised optimal solution. The main idea of this research work is to handle a constrained multi-objective optimization problem using NSGA-II, for NOVA parallel HEV transit bus parameters. More detailed work of NOVA parallel hybrid transit bus design optimization can be found in chapter 4.

2.3 SUMMARY

An HEV optimization problem is formulated as a constrained nonlinear optimization problem. Many classic, gradient-based and derivative-free methods of optimization have been proposed. Most of them repeat multiple simulations with different weights and constraint values to identify multiple trade-off solutions. This approach is effective only when suitable weights and constraint bounds are capable of accurately indicating the desired compromised among the design. However, there exist a few disadvantages using this approach:

(1) Requires strong assumptions for the objective function so that appropriate weights associated with objectives can be specified;

(2) Single solution for each objective optimization problem is obtained without any other information about trade-off among objectives;

(3) Weighted sum and ε-constraint strategy may result in a suboptimal solution, if the objectives trade-off results in non-continuous and/or non-convex behaviour in function space;

(4) Methods work on pre-defined rules. Hence, the method can only be efficient in solving a special class of problem and cannot be applied to a wide variety of problems.

However, population based MOEAs project a tremendous potential for HEV design problems; involve numerous local minima, discontinuity in objective function, and nonlinear constraints. Moreover, MOEAs do not require any user dependent artificial fix-up or information about derivative of objectives. It can find multiple trade-off solutions in a single simulation run.

CHAPTER 3

OVERVIEW OF HYBRID ELECTRIC VEHICLE CONTROL STRATEGIES

3.1 INTRODUCTION

HEVs can significantly improve fuel economy and reduce emissions with satisfactory vehicle performance [3]. Typical HEVs consist of an internal combustion engine (ICE), electric motor (EM), single or multiple energy storage systems (ESS), power electronic converters, and controllers. Regardless of the HEV architecture employed, critical tasks in the control of an HEV include optimal power spilt between ICE and EM as well as smart and efficient co-ordination between multiple energy sources and converters. To monitor these aspects, implementation of an intelligent control strategy is inevitable. Control strategies (CS) for HEVs are sets of algorithms implemented in the vehicle master controller, which optimally controls the generation and the flow of power between drivetrain components. Fig. 3-1 displays a typical HEV layout, with energy management controller. Inputs to the energy management controller are the drive's power demand, vehicle speed or acceleration, energy storage state of charge, present road load and even sometimes the information about future traffic conditions from Global Positioning System (GPS). The outputs of the energy management controller are decisions to turn-off or turn-on of the drivetrain components, the transition of their operating points by commanding subsystem controllers to achieve best performance and overall system efficiency. Due to the complex structure of HEVs, the design of control strategies presents a considerable challenge. The preliminary objective of the control strategy is to satisfy the driver's power demand, while minimizing fuel consumption and emissions, without compromising vehicle performance constraints, such as acceleration, gradeability, and regulation of ESS state of charge (SOC). Moreover, fuel economy and emissions minimization are conflicting objectives, a smart control strategy should satisfy a tradeoff among them.

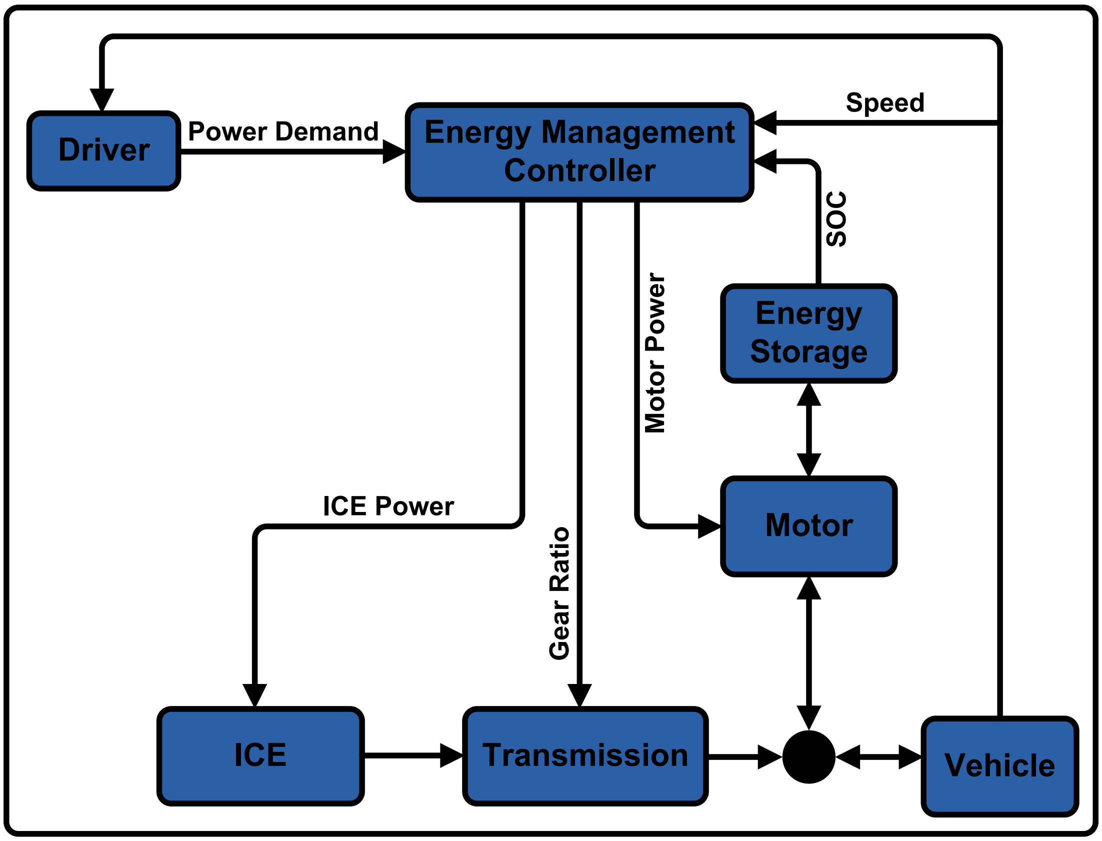


Fig. 3-1 Energy management controller layout

In this chapter, various HEV control strategies will initially be reviewed and categorized. A detailed overview of different existing control strategies along with their respective merits and demerits will be presented. The overall effect of different control strategies on HEV drivetrain efficiency will be focused upon, and the compatibility of optimal CS options for parallel HEV drivetrains will be investigated. A broad classification of HEV control strategies is presented in Fig. 3-2. HEV control strategies

(CS) are broadly classified into rule-based CS and optimization-based CS and all other subcategories are classified based on these two main categories.

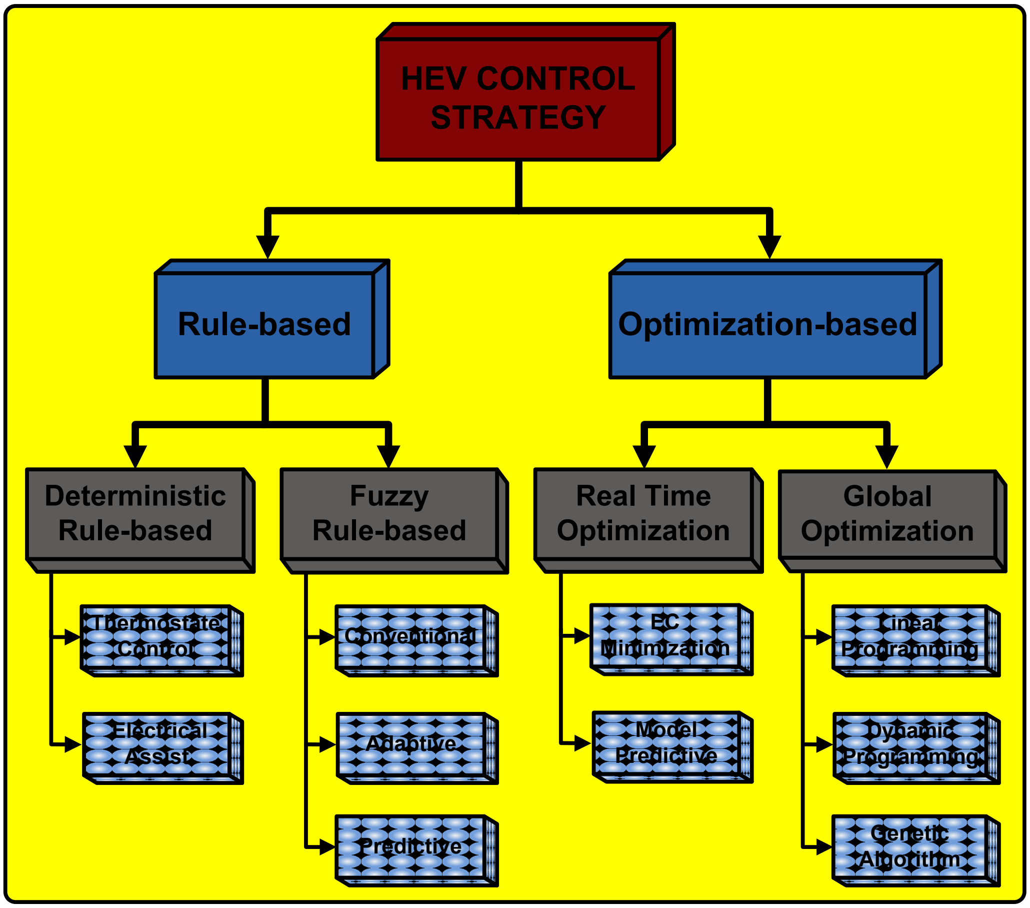


Fig. 3-2 Classification of hybrid electric vehicle control strategies

3.2 RULE-BASED CONTROL STRATEGIES

Rule-based control strategies are fundamental control schemes that depend on mode of operation. They can be easily implemented with real-time supervisory control, to manage power flow in a hybrid drivetrain. The rules are determined based on human intelligence, heuristics, or mathematical models and generally, without a beforehand knowledge of a predefined drive cycle. Most of the described rule-based (RB) control strategies are based on 'IF-THEN' type of control rules and perform load balancing within the vehicle [17], [18]. The main goal of load balancing is to move ICE operation closer to optimal region of fuel economy, efficiency, and emissions at particular ICE speed. However, for this type of system, fairly good fuel economy can be found at lower engine torques and speeds than the best efficiency. Thus, small acceleration demand can result in higher fuel economy [19]. The difference between driver's power demand and ICE generated power is compensated by using EM or utilized to charge by using EM as generator. This strategy is further subcategorized into deterministic rule-based and fuzzy rule-based and these approaches are discussed in following subsections.

3.2.1 Deterministic Rule-based Control Strategies

The rules are designed with the aid of fuel economy or emission data, ICE operating maps, power flows within the drivetrain, and driving experience. Implementation of rules is performed via lookup tables, to share the power demand between the ICE and the electric traction motor.

3.2.1.1 Thermostat Control Strategy

The thermostat control strategy uses the generator and ICE to generate electrical energy used by the vehicle. In this simple control strategy the battery state of charge (SOC) is always maintained between predefined high and low levels, by simply turning on or off the ICE [3]. Although the strategy is simple but it is unable to supply necessary power demand in all operating modes. This strategy is very effective for a series hybrid city transit bus running on prescheduled driving routes.

3.2.1.2 ELECTRIC ASSIST CONTROL STRATEGY

The most successful commercially available HEVs have adopted electric assist control strategy approach [20]. In this strategy the ICE works as the main source of power supply and electric motor is used to supply additional power when demanded by the vehicle. Due to charge sustaining operation, the battery SOC is maintained during all operating modes. The electrical assisted control strategy works on following rules:

(1) Below certain minimum vehicle speed, the vehicle works as a pure Electric Vehicle (EV), and only the electric motor is supplying total power;

(2) The electric motor is used for power assist, if the required power is greater than the maximum engine power, at the engine's operating speed;

(3) To avoid inefficient operation, the ICE turns off, if the power required is below minimum limit, and the electric motor will produce the required power;

(4) Motor charges the battery during regenerative braking events;

(5) When battery SOC is lower than its set minimum value (cs_lo_soc), the ICE produces extra torque to sustain battery SOC.

ICE operation modes are shown in Fig. 3-3 and Fig. 3-4. Fig. 3-3 represents the ICE operation when current battery SOC > (cs_lo_soc). In this situation EM delivers power to keep ICE operation in efficient region. To avoid inefficient operation of ICE, ICE should turn off when (a) vehicle speed < cs_elec_launch_speed and (b) add_trq + cs_charge_trq < ICE off torque. ICE off torque is obtained by equation (3-1)

$$\tau_{ICE\ off} = \tau_{off\ frac.} \times \tau_{max} \tag{3-1}$$

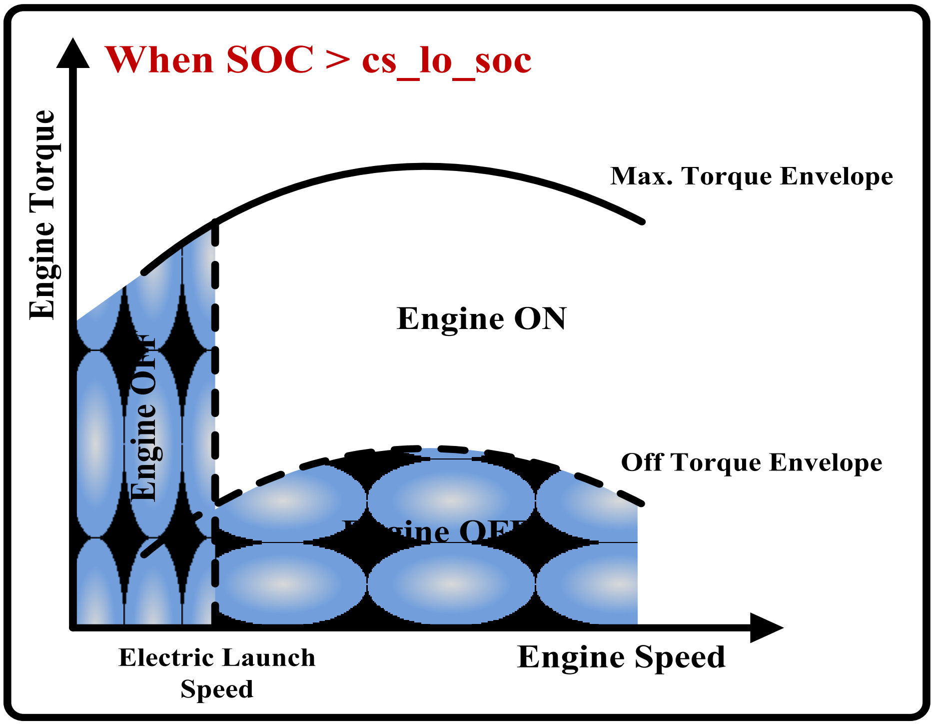


Fig. 3-3 Engine operation when SOC > (cs_lo_soc)

However, if current SOC is lower than (cs_lo_soc), the situation is a little complex. In Fig 3-4, if the requested engine torque is at the operation point "A," the engine will work at point "B" since it must provide the additional power to charge the battery. Required additional torque from ICE is calculated using equation (3-2). This additional charging torque is proportional to the difference between actual SOC and the average of (cs_lo_soc) and (cs_hi_soc).

$$\tau_{additional} = \tau_{charge} \times \left[\frac{cs\_lo\_soc + cs\_hi\_hoc}{2} - SOC\right] \qquad (3\text{-}2)$$

Also, if the requested torque is at point "C", and this torque plus the additional charge torque is below the "Minimum Torque Envelop", the ICE will work at minimum ICE efficiency operating point "E" instead of "D". Minimum efficiency operating point is calculated using equation (3-3)

$\tau_{\text{min. efficiency}} = \tau_{\text{min. frac.}} \times \tau_{\text{max}}$ (3-3)

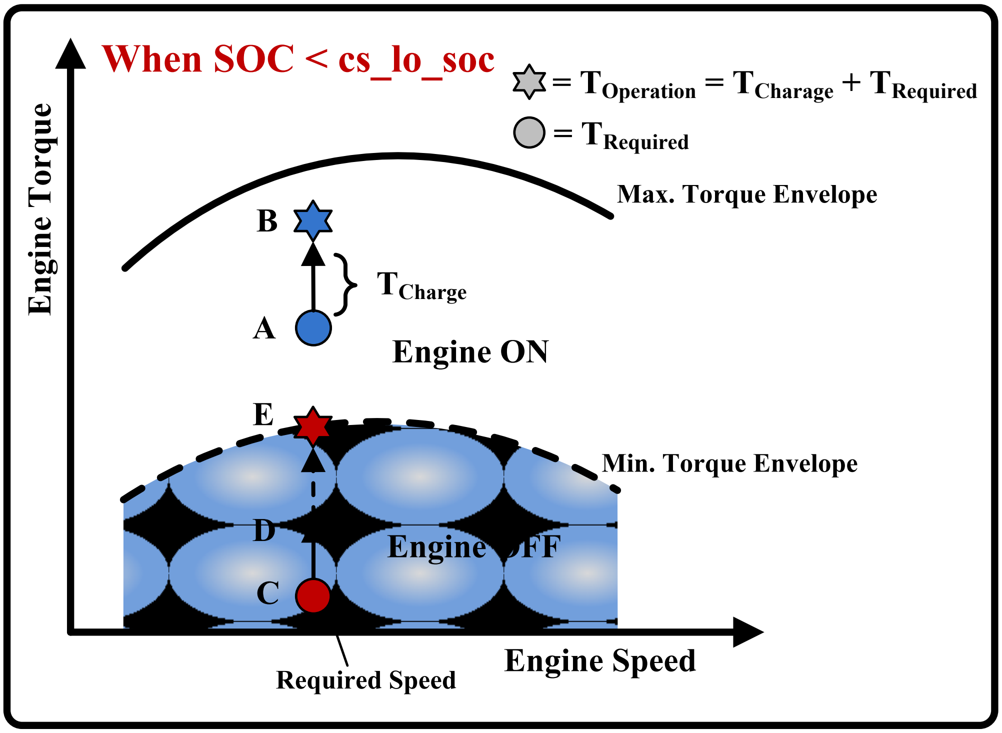


Fig. 3-4 Engine operation when SOC < (cs_lo_soc)

3.2.2 Fuzzy Rule-based Control Strategies

Fuzzy systems are knowledge-based or rule-based systems. The knowledge of an expert can be used to form a rule base and by utilizing decision making quality of fuzzy logic, a real time control can also be realized [21]. Fuzzy logics are non-linear structure with robustness against imprecise measurement and component variability and if required they can be tuned and adapted easily, thus increasing the degree of freedom of control. Due to the highly nonlinear, time varying nature of the parallel HEV drivetrain, control strategy implementation using fuzzy logic control is one of the most reasonable methods to handle HEV energy management problems [22].

3.2.2.1 TRADITIONAL FUZZY CONTROL STRATEGY

Efficiency is decided based on the selection of input, output, and rule-base of this control strategy [23]. Two operating modes; namely, optimum fuel-use and fuzzy efficiency modes, are used to control drivetrain operation. The fuzzy logic controller accepts battery SOC and the desired ICE torque as inputs. Based on these inputs as well as the selected mode, the ICE operating point is set. Power requested by the electric traction motor is the difference of total load power request and power requested from ICE, which can be calculated from Equation (3-4).

$$P_{EM} = P_{LOAD} - P_{ICE} \tag{3-4}$$

In the optimum fuel-use strategy, the fuzzy logic controller limits instantaneous fuel consumption, calculated from the fuel-use map, and maintains sufficient battery SOC, while delivering demanded torque. Inputs to the controller are an error between the desired fuel consumption and actual fuel consumption, the total power demanded, as well as the battery SOC, as shown in Fig. 3-5. However, this strategy does not consider ICE efficiency maps.

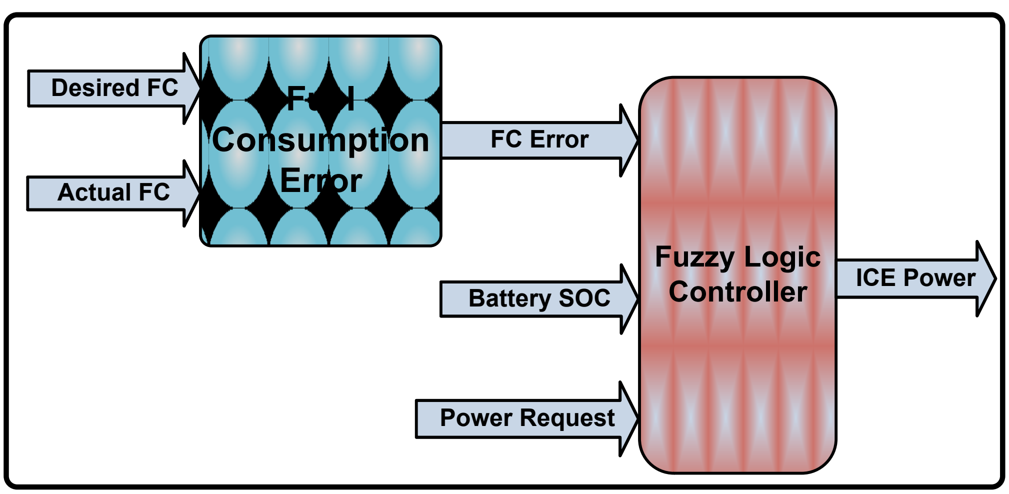


Fig. 3-5 Fuel-optimized fuzzy logic controller

In the fuzzy efficiency strategy, the ICE is operated in its most efficient operating region. The operating points of the ICE are set near the torque region, where efficiency is the maximum, at particular engine speed [24]. Load balancing is achieved by using the electric motor. This CS uses the motor to force the ICE to operate in the region of minimal fuel consumption, while maintaining SOC in battery. Load balancing is necessary to meet power demand and avoid unnecessary charging and discharging of the ESS. A major drawback of this CS is that the peak efficiency points are near the high torque region, whereby the ICE generates more torque than required, which in turn increases fuel consumption. Also, during load balancing, heavy regeneration over charges the ESS. To avoid this scenario, this CS should be used with a downsized ICE [20].

3.2.2.2 ADAPTIVE FUZZY CONTROL STRATEGY

With this strategy, both fuel efficiency and emissions can be optimized simultaneously. However, fuel economy and emissions are conflicting objectives, which means an optimal solution cannot be achieved to the satisfaction of all objectives. The optimal operating point can be obtained using weighted-sum approach optimization of conflicting objectives. Due to various driving conditions, appropriate weights have to be tuned for fuel economy and emissions. Within areas with stringent air pollution laws, operating points with high emissions are heavily penalized. The conflicting objectives within the adaptive fuzzy logic controller, presented in [25], include fuel economy, NO_X, CO, and HC emissions. However, due to different dimensions, the values of fuel economy and emissions cannot be directly compared with one another. In order to weigh the interrelationship of the four contending optimising objectives with a uniform standard, it is essential to normalise the values of fuel economy and emissions by utilising the optimal values of fuel consumption and emissions at current speed. Optimal values of fuel economy and emissions at particular ICE speed can be obtained from ICE data map.

The overall problem formulation is described by Equation (3-5), where *J* is the cost function, parameters $\overline{\eta}$, $\overline{NO_X}$, $\overline{HC}$, $\overline{CO}$ are normalized values of efficiency, NO_X, CO, and HC emissions, respectively, and w_i are weights.

$$\min\ J = W_1\left(1 - \overline{\eta}\right) + W_2\overline{NO_X} + W_3\overline{HC} + W_3\overline{CO} \tag{3-5}$$

Relative weights are adaptively assigned to each parameter based on their importance in different driving environments. Moreover, weights must be selected for each ICE, based on their individual data maps. This control strategy is able to control any one of the objectives, by changing the values of relative weights. Furthermore, tremendous reduction in vehicle emission is achieved, with negligible compromise in fuel economy.

3.2.2.3 PREDICTIVE FUZZY CONTROL STRATEGY

If information of the driving trip is prior knowledge, it is extremely trivial to obtain a global optimum solution, to minimize fuel consumption and emissions. However, primary obstacles entailed include acquiring future information of planned driving routes and performing real-time control. With the aid of a Global Positioning System (GPS), this problem can be bypassed, with knowledge of the type of obstacles that will be faced in the near future, such as heavy traffic or a steep grade. Thereafter, control actions can be executed, to account for specific situations. For example, if the vehicle is on a highway, entering a city, where heavy traffic may be encountered, it is an intelligent decision to restore more energy, by charging the batteries, for later use, in possibly all-electric city driving conditions. A predictive control strategy is proposed in [25], to achieve a higher degree of control over the fuel economy and emissions. A general overview of the concept is shown in Fig.3-6

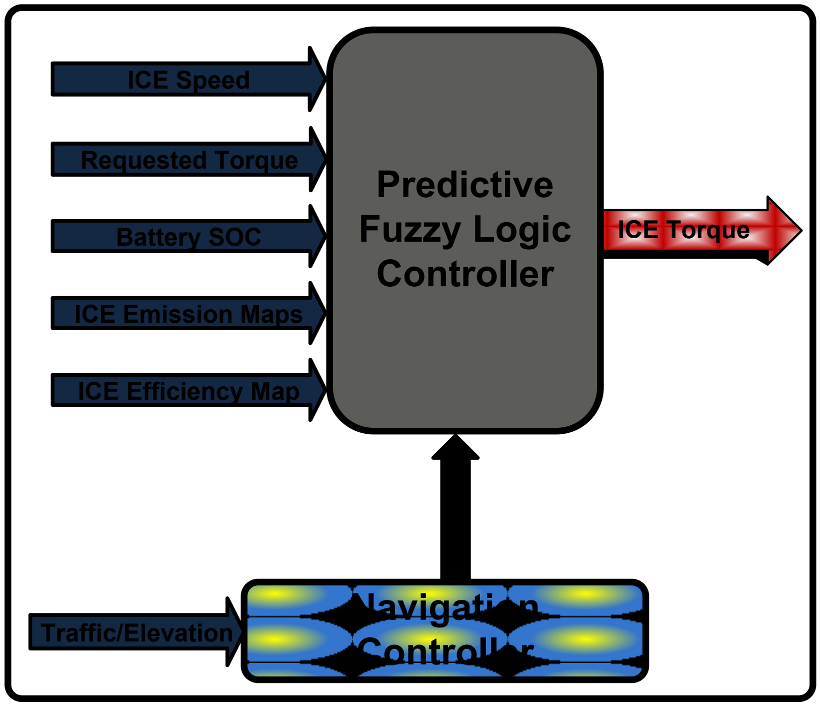


Fig. 3-6 Structure of fuzzy predictive controller

General inputs to the predictive fuzzy logic controller are vehicle speed variation corresponding to recent speeds, the speed state of the vehicle in a look-ahead window, and elevation of sampled points along a predetermined route, from the GPS. Based on available history of vehicle motion and the possible changes to vehicle motion in the near future, the fuzzy logic controller starts to calculate the optimal ICE torque contribution for the current vehicle speed. Supplied information of the future is a sampled set in a look-ahead window, along a planned driving route. The output of the predictive fuzzy logic controller is a normalized GPS signal in (−1, +1), which informs the master controller to charge or discharge the batteries, to restore enough energy for future vehicle operating modes. For example, if the navigation system indicates an "uphill grade" and "slow traffic," the predictive controller commands the main controller to charge batteries instantaneously.

3.3 OPTIMIZATION-BASED CONTROL STRATEGIES

In optimization-based control strategies, the reference of the optimal torques and optimal gear ratios can be found by minimizing the cost functions of fuel consumption and/or emissions. Global optimum solutions can be obtained by performing optimization over a fixed driving cycle. However, with these control techniques, real-time energy management is not directly possible. At the same time, the results of these strategies could be used to compare the features of other control strategies [26], and also as base to define rules for online implementation. Also, on basis of an instantaneous cost function, a control strategy based on a real time optimization can be obtained. This instantaneous cost function relies on the system variables at the current time only and also, to guarantee the self-sustainability of the electrical path it should include equivalent fuel consumption. Although the solution obtained with such strategy is not globally optimal, but it can be utilized for real time implementation.

3.3.1 GLOBAL OPTIMIZATION

Global Optimization technique requires the knowledge of the entire driving pattern. It includes battery SOC, driving conditions, driver response, and route prediction. This method can be a good analysis, design, and assessment tool for other control strategies. However, due to computational complexity, they are not easily implementable for practical applications. Linear programming [27], dynamic programming [28], and genetic algorithms [29] etc. are used to resolve vehicle energy management issues.

3.3.1.1 LINEAR PROGRAMMING

Energy management in an HEV using the Linear Programming (LP) technique is introduced in [27]. The problem of optimization of fuel economy is considered as a convex nonlinear optimization problem, which is finally approximated by a linear programming method. More specifically, LP is mostly used for fuel efficiency optimization in series HEV topologies. Formulation of fuel economy improvement problem as an LP can obtain globally optimal solution. However, approximate formulation of the problem restricts the application of LP to merely the uncomplicated series HEV architecture.

3.3.1.2 DYNAMIC PROGRAMMING

The dynamic programming (DP) technique was originally developed by Bellman, to find optimal control policies for multi-stage decision processes. Opposite to the rule-based algorithm, the dynamic optimization approach generally depends on a model to compute the best control strategy. Analytical or numerical models can be used. For a particular driving cycle, the optimal control strategy to achieve the best fuel economy can be obtained by solving a dynamic optimization problem. References [28] and [31] utilize the DP technique to solve the optimal power management problem of an HEV, by minimizing a cost function over a fixed driving cycle. To reduce the computational burden of the DP, they include only fuel consumption, NOx and PM emissions of the vehicle as state variables.

This technique can efficiently handle nonlinearity, while searching a global optimum solution. It can also provide a logical approach for optimal HEV power distribution. However, computational complexity of the programming method is a major constraint.

3.3.1.3 GENETIC ALGORITHM

Genetic algorithms (GA) are stochastic global search techniques, which mimic the process of natural biological evolution (survival of the fittest). They have been proven to be effective to solve complex engineering optimization problems, characterized by nonlinear, multi-modal, non-convex objective functions. GA is efficient at searching the global optima, without getting stuck in local optima [32].

The process begins with a set of potential solutions or chromosomes (usually in the form of bit strings) that are randomly generated or selected. The entire set of chromosomes forms a population. The chromosomes evolve during several iterations or generations. Three commonly used operations are employed: reproduction, crossover, and mutation. These 3 operators are applied, in turn, to the solutions in the current generation, during the search process. The chromosomes are then evaluated using a certain fitness criteria and the best ones are selected, while the others are discarded. This process repeats until one chromosome has the best fitness, and thus, is chosen as the best solution of the problem [33]. Unlike the conventional gradient based method, the GA technique does not require any strong assumption or additional information of objective parameters. GA can also explore the solution space very efficiently. However, this method is very time consuming, and does not provide a broader view to the designer.

3.3.2 Real-time Optimization

Due to the causal nature of global optimization techniques, they are not suitable for real-time analysis. The main aim is to reduce global criterion to an instantaneous optimization, by introducing a cost function that depends only on the present state of the system parameters [34]. Moreover, global optimization techniques do not consider variations of battery SOC in the problem. Hence, in order to derive cost functions for instantaneous optimization of power split, while maintaining battery charge, real-time optimization is performed.

3.3.2.1 Real-time Equivalent Consumption Minimization Scheme (ECMS)

References [34]-[36] introduce the application of optimal control theory for real-time energy management of HEVs. Equivalent fuel consumption is the extra fuel required to charge the battery. On this basis, an instantaneous cost function can be calculated and minimized, by selecting a proper value for torque split control variable. The total equivalent fuel consumption is the sum of the real fuel consumption of ICE and the equivalent fuel consumption of electric motor. This allows a unified representation of both the energy used in the battery and the ICE fuel consumption. Reference [35] approaches this problem by calculating the equivalent fuel consumption, using mean efficiencies.

Using this method, equivalent fuel consumption is calculated on a real-time basis, as a function of the current system measured parameters. No future predictions are necessary and only a few control parameters are required, which vary from one HEV topology to another, as a function of the driving conditions. The only disadvantage of this strategy is that it does not guarantee charge-sustainability of the plant.

3.3.2.2 MODEL PREDICTIVE CONTROL

The equivalent fuel consumption, represented by a cost function over a look-ahead window, to find a real-time predictive optimal control law, was introduced in [37]. The information supplied by the navigation system, corresponding to future states, is a sampled set in a look-ahead window, along a planned route. The value of the look-ahead window length and the number of samples in the region are set, based on optimal values for a given drive cycle and vehicle configuration. At each sampled point, traffic information, such as speed of the vehicle and elevation at that point, are collected. The speed state of the vehicle and elevation in the look-ahead zone are selected as the average of the sampled points. Optimal control theory is proposed to solve such a problem. This approach, which utilizes the preview driving pattern and route information, depicts superior fuel economy. A sample look-ahead window is shown in Fig. 3-7.

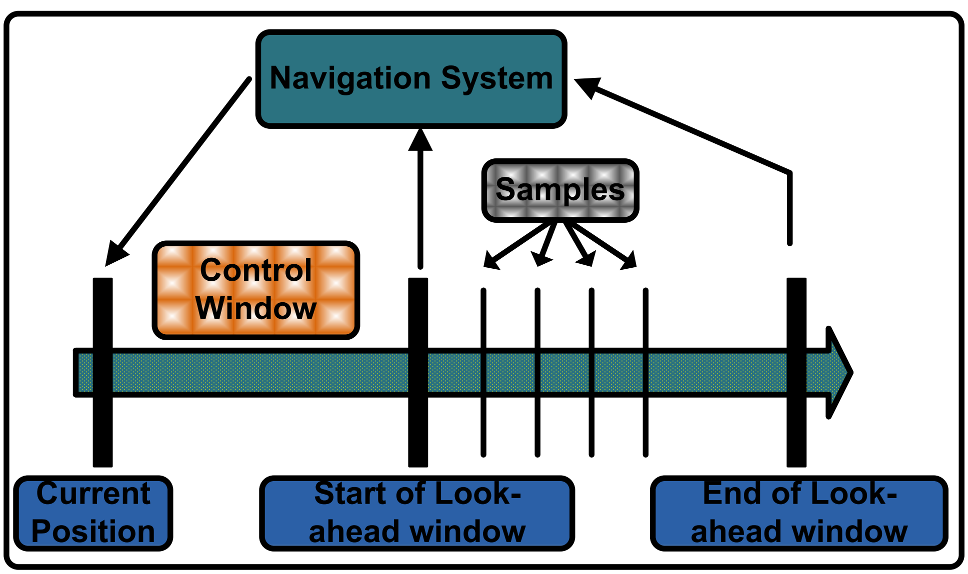


Fig. 3-7 Look-ahead window for predictive control

3.4 SUMMARY

In this chapter, various hybrid electric vehicle energy management control strategies were discussed and contrasted in detail. The control strategies discussed varied from traditional on-off type thermostat control to advanced model predictive and adaptive control. In general, HEV control strategies were classified as rule-based and optimization-based. The classified control strategies were discussed, in general, and their sub-categories were introduced briefly, whereby their merits and demerits were highlighted. A comparative summary of global optimization techniques are listed in Table 3-1.

Table 3-1 Comparison of optimization-based control strategy

Technique	Robustness	Real-time Capability	Computation Intensity	Complex Structure
Linear Programming	-	- -	+ +	-
Dynamic Programming	-	-	-	+
Genetic Algorithm	+	-	-	+ +

Although global optimization-based strategies cannot be used in real-time applications, but they provide a solid platform for design and comparison. From an online implementation point of view, optimal real-time and fuzzy rule-based methods are deemed highly suitable. Because of their adaptive and robust characteristics, fuzzy rule-based control strategies are superior, compared to deterministic rule-based methods.

Following points should be taken into consideration while comparing HEV energy management control strategies:

a) Computational complexity is a major issue in analytical optimal control methods, since they are more memory intensive than fuzzy rule-based methods.

b) Since analytical optimal methods are based on drivetrain models, any uncertainties in modeling would affect the controller. On the other hand, fuzzy rule-based methods are robust and insensitive to modelling uncertainties.

c) Information from the navigation system can be used for predictive and future control. However, this not only increases the number of inputs, but also makes for a much more complicated rule-based system. Nevertheless, the analytical optimal controller can obtain a semi-global solution without any complexity.

d) Much more complicated controllers would be needed for complex HEV drivetrains. On the other hand, fuzzy rule-based methods are more flexible.

Although the listed control strategies provide a fairly strong comparative view to the EV/HEV designer, there exist a few important points that can be considered for future development work. Energy storage devices are vital elements of EV/HEV drivetrains. Payback period, maintenance cost, and replacement cost of energy storage devices are strongly dependent on durability of these devices. Hence, it is advisable to design a control strategy keeping in mind extension of durability of the energy storage system. In future all-electric and plug-in electric vehicle architectures, additional energy storage components, such as ultra-capacitors and flywheels will most definitely be incorporated, which will require innovative and efficient power management strategies.

CHAPTER 4

MULTI-OBJECTIVE OPTIMIZATION OF NOVA PARALLEL HYBRID TRANSIT BUS

4.1 INTRODUCTION

In chapter 2, the HEV optimization problem is formulated as a constrained nonlinear optimization problem. Many classic, gradient-based and derivative-free methods of optimization have been proposed to handle HEV optimization problem. They repeat multiple simulations with different weights and constraint values, to identify multiple trade-off solutions. These approaches are effective only when suitable weights and constraint bounds are capable of accurately indicating the desired compromise among the design. Moreover, these methods require strong assumptions for the objective function, so that appropriate weights associated with objectives can be specified. A single solution for each objective optimization problem is obtained without any other information about trade-off among objectives.

Gradient based methods are not efficient for HEV parameter optimization, since they require derivative information of objective function. However, derivative-free DIRECT search method is more efficient than gradient-based SQP. However, this optimization method requires a large number of function evaluations and they show slow convergence.

However, population based MOEAs project a tremendous potential for HEV design problems; they involve numerous local minima, discontinuity in objective function, and nonlinear constraints. Moreover, MOEAs do not require any user dependent artificial fix-up, information about derivative of objectives, and can find multiple trade-off solutions in a single simulation run.

In this chapter, parameter optimization of NOVA parallel hybrid electric transit bus, using one the most efficient multi-objective optimization algorithm, NSGA-II, is devised. The algorithm considers fuel economy as well as emissions as design objectives, drivetrain component and control strategy parameters as design variables, and vehicle acceleration and gradeability performance criterions as constraints. Performance of the NOVA parallel hybrid electric transit bus is evaluated using the Advanced Vehicle Simulator (ADVISOR) software [20].

Moreover, in this chapter, the basics and applications of multi-objective genetic algorithm (MOGA) in the proposed design problem are explained. Multi-objective problem of NOVA parallel hybrid transit bus is formulated. Modeling and simulations as well as performance of NOVA parallel hybrid transit bus parameters optimization are analyzed for different drive cycles.

4.2 VEHICLE MODELING AND CONTROL STRATEGY

4.2.1 PARALLEL HYBRID ELECTRIC TRANSIT BUS DRIVETRAIN

The drivetrain of a parallel HEV is illustrated in Fig. 4-1. For modeling and simulation, a NOVA low floor transit bus database, available in ADVISOR, is used. In a parallel HEV, both the internal combustion engine (ICE) and the electric motor (EM) deliver power to the wheel. The electric motor works as a generator either during regenerative braking or while absorbing additional power from the ICE. In this case, the output of ICE is greater than the required power to drive the vehicle, and energy storage state of charge is below the maximum level [3]. In some cases, ultra-capacitors and/or flywheels can be hybridized with a battery pack, to further enhance vehicle dynamic performance.

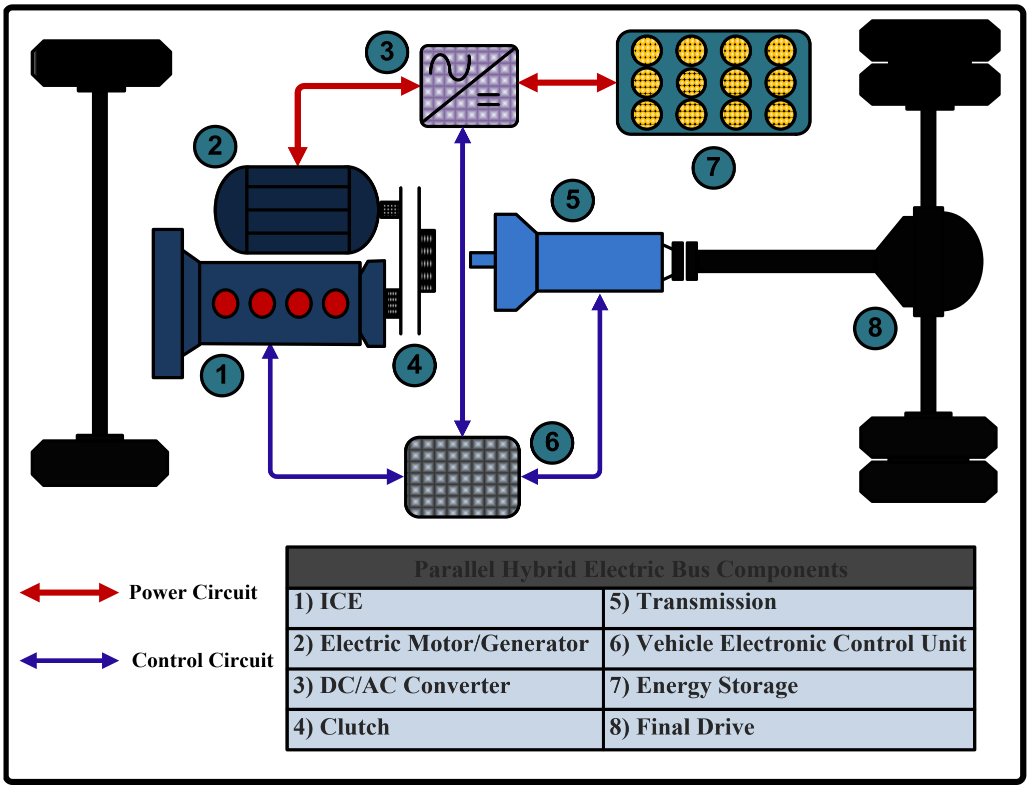


Fig. 4-1 NOVA parallel HEV transit bus drivetrain

High energy density, long life, and reasonable cost make nickel-metal hydride (Ni-MH) batteries the first choice as the energy storage system (ESS). The drivetrain component sizing depends mainly on the driving requirement of the vehicle. The modeled vehicle is tested on the Urban Dynamometer Driving Schedule (UDDS), Montreal Pie-IX 139 bus drive cycle, and the New York bus drive cycle. NOVA bus drivetrain components and parameters are listed in Table 4-1 and Table 4-2, respectively. Table 4-3 presents bus performance parameters.

Table 4-1 NOVA parallel hybrid electric transit bus drivetrain components

No	Component	Specifications
1	Engine	*Cummins* ISL 208kW, 8.9L Diesel Engine
2	Electric motor	*Westinghouse* AC Induction motor
3	Energy storage	*Ovonic* 60 Ah Ni-MH HEV battery, 40 Modules
4	Transmission	*ZF* Auto Transmission ZF5HP590AT

Table 4-2 NOVA parallel hybrid electric transit bus parameters

No	Vehicle Type	NOVA Low Floor Transit Bus
1	Vehicle mass	18449 kg
2	Frontal area	8.0942 m^2
3	Coefficient of drag	0.79
4	Wheel base	6.19 m
5	Wheel radius	0.5 m
6	Rolling resistance coefficient	0.00938

Table 4-3 NOVA parallel hybrid electric transit bus performance parameters

No	Performance Parameter	Value
1	Acceleration	0 – 80 km/h < 50 sec
2	Gradeability	@ 16 km/h, for 20 sec > 10 %

4.2.2 Parallel Hybrid Control Strategy

HEVs principally employ one or more energy sources for propulsion, which require an intelligent power management scheme, known as the control strategy (CS), for optimal power sharing among them. These control strategies are sets of algorithms implemented in the vehicle master controller [38]. Moreover, the CS has considerable effects on the performance of the vehicle. Hence, an optimal control strategy plays a vital role in improving overall performance. In this research work, parameter optimization of NOVA parallel transit bus using NSGA-II is analyzed using parallel electric assist and fuzzy logic based fuzzy efficiency control strategies. Both control strategies are rule-based, charge sustaining CS and perform load balancing in the vehicle. Moreover, in both control strategies, the ICE works as the main source of power supply, and the EM is used to supply additional power, when demanded by the vehicle. Due to charge sustaining operation, the battery SOC is maintained during all operating modes. Both electric assist and fuzzy efficiency control strategy were earlier described, in chapter 3. The parameters of both control strategies are listed in Table 4-4.

Table 4-4 Parallel electric assist and fuzzy efficiency control strategy parameters

No	Parameters	Description
1	cs_lo_soc	Lowest desired battery state of charge
2	cs_hi_soc	Highest desired battery state of charge
3	cs_electric_launch_speed_lo	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at low battery SOC
4	cs_electric_launch_speed_hi	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at high battery SOC
4	cs_charge_trq	Additional torque required from engine to charge or discharge the battery based on battery SOC
5	cs_off_trq_frac	Fraction of ICE maximum torque at each speed at which the ICE should turn off when SOC > (cs_lo_soc)
6	cs_min_trq_frac	Fraction of ICE maximum torque at each speed above which ICE must operate if SOC < (cs_lo_soc)

4.3 MULTI-OBJECTIVE GENETIC ALGORITHM

Most real-world engineering problems involve simultaneous optimization of multiple objectives. Moreover, because of conflicting multiple objectives, a multi-objective optimization problem results in a number of optimal solutions, known as trade-off or pareto-optimal solutions. Without any further (higher level) information on a problem, any one of these trade-off solutions cannot be treated superior than the other. Classic optimization methods follow pre-defined search rules, and convert the multi-objective optimization problem into a single-objective optimization, using an artificial fix-up, and can obtain only one trade-off solution in a single simulation run. To obtain different trade-off solutions, using classic methods, users have to run the simulation multiple times, with different values of artificial fix-up. Therefore, to eliminate these issues, deterministic classic search methods have been replaced by population-based multi-objective evolutionary optimization methods, which can find multiple trade-off solutions in a single simulation run. Moreover, these methods use the concept of dominance in their search, and they have been proven to be an effective strategy to solve complex engineering optimization problems, characterized by non-linear and non-convex objective functions.

4.3.1 PARETO-OPTIMAL SOLUTION

A set of solutions is said to be pareto-optimal, if any improvement in one of the objectives inevitably leads to deterioration of at least one of the other objectives. Fig. 4-2 illustrates a set of solutions of a two-objective problem. It is clear from the figure that, solution "O" cannot be treated as optimal, since solution "X" is better than "O" in both objectives. All feasible solutions of search space are inferior in both objectives to those lying on the curve "VWXYZ". Thus, solutions of the curve "VWXYZ" are optimal solutions, and termed as "Pareto-optimal" or "trade-off" solutions. The curve "VWXYZ" is known as the pareto-optimal front.

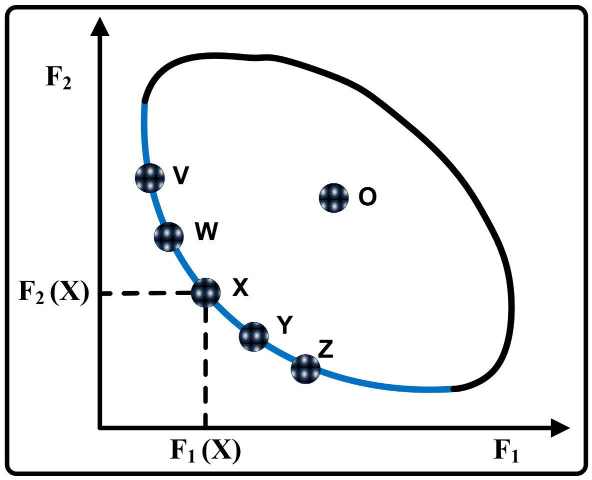


Fig. 4-2 Pareto optimal front

Evolutionary Algorithms (EAs) are population based stochastic global search techniques, which mimic the process of natural biological evolution (survival of the fittest). Since EAs work with a population of solutions, a simple EA can be used to find multiple pareto-optimal solutions in a single simulation run. While dealing with a multi-objective optimization problem, users are interested in finding as many pareto-optimal solutions as they can, and the obtained pareto-optimal solutions must be sparsely spaced in the pareto-optimal region. Thus, there exist two important goals of an ideal multi-objective optimization algorithm:

1) To find a set of solutions as close as possible to the pareto-optimal front;

2) To find a set of solutions as diverse as possible.

Over the past decade, a number of multi-objective evolutionary algorithms (MOEAs) have been suggested, to find multiple pareto-optimal solutions in a single simulation run [11]. The concept of non-domination and explicit diversity preserving operator were initially introduced in one of the first Non-dominated Sorting Genetic Algorithm (NSGA) [39]. However, this approach has high computational complexity of non-dominated sorting, including lack of elitism and specification of the sharing parameter (σ share). An improved version of NSGA, utilizing parameter-less elitist approach, named NSGA-II, was proposed in [40]. In the study of Zitzler, Deb, and Theile [41], it was clearly shown that elitism helps in achieving better convergence in MOEAs. The simulation results of NSGA-II for a number of difficult test problems outperformed its two contemporary MOEAs, the pareto-archived evolution strategy (PAES), as well as the strength-pareto EA (SPEA), in terms of finding a diverse set of solutions and converging near the true pareto-optimal set [42], [43].

The NSGA-II adopts a non-dominated sorting procedure for unconstrained MOOPs and a non-constrain-dominated sorting procedure for constrained MOOPs, to distinguish the closeness of the solutions to the pareto front. It also suggests an elite-preserving strategy, to guarantee convergence. The diversity of the solutions is maintained by a crowding distance technique. The constraint multi-objective optimization is extremely essential in this research work, from the point of view of NOVA parallel hybrid electric transit bus parameter optimization. The advantages and simple methodology of NSGA-II encourages the use of the NSGA-II optimization method in this research work. The algorithm is outlined in the following subsection.

4.3.2 NSGA-II PROCEDURE

Initially, a random parent population, P_0, is created. The parent population is sorted based on non-domination. Each solution is assigned fitness equal to the level of non-domination (Level 1 is the best level). In this manner, minimization of fitness is assumed. An offspring population, Q_0, of size N is created, using binary tournament selection, crossover, and mutation. Since the elitism is introduced by comparing current populations with previously found best non-dominated solutions, the procedure is different after the first generation, and onwards. The elitism procedure for $t \geq 1$ and for a particular generation is described in Table 4-5.

Table 4-5 NSGA-II elitism procedure

$R_t = P_t \cup Q_t$	Combine Parent and offspring population
$\mathcal{F}$ = Fast- non dominated-sort (R_t)	F=(F_1, F_2,..), all non dominated fronts of R_t
$P_{t+1} = \phi$ and i=1	
Until $P_{t+1} + F_i \leq N$	Until the parent population is filled
Crowding distance- assignment (F_i)	Calculate crowding-distance in (F_i)
$P_{t+1} = P_{t+1} \cup F_i$	include i^{th} non dominated front in the parent populations
i=i +1	Check the next front for inclusion
Sort (F_i, $\prec_n$)	Sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1} \cup F_i$ [1: (N - $\lvert P_{t+1} \rvert$)]	choose the first (N - $\lvert P_{t+1} \rvert$) elements of F_i
Q_{t+1}= make new population (P_{t+1})	Use selection, crossover and mutation to create a new population Q_{t+1}
t = t +1	Increment the generation counter

At any generation, t, the offspring population, Q_t, is created by using P_t parents and usual genetic operators like selection, crossover, and mutation. Thereafter, population P_t and Q_t are combined together, to form a new population, R_t, of size 2N. Then, the population R_t is classified into different non-domination classes. Thereafter, the new population is filled by points of different non-domination fronts, one at a time. The filling starts with the first non-domination front (of class one) and continues with points of the second non-domination front, and so on. Since the overall population size of R_t is 2N, not all fronts can be accommodated in N slots available for the new population. All fronts which could not be accommodated are deleted. This scenario is illustrated in Fig. 4-3.

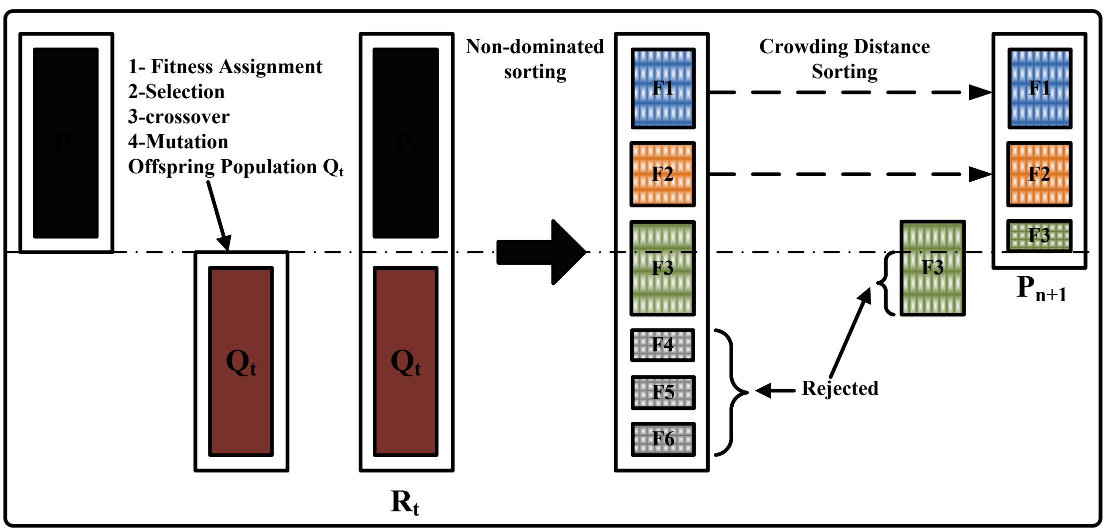


Fig. 4-3 NSGA-II Procedure

4.3.3 Crowding Distance Calculation

The crowded-sorting of the points of the last front, which could not be included fully, is achieved in the descending order of their crowding distance values and points from the top of the ordered list. The crowding distance, di, of point i, is a measure of the objective space around point i, which is not occupied by any other solution in the population. The crowding distance, di, of a point in NSGA-II, is the perimeter of the cuboid, as shown in Fig. 4-4 formed by using the nearest neighbors in the objective space as the vertices.

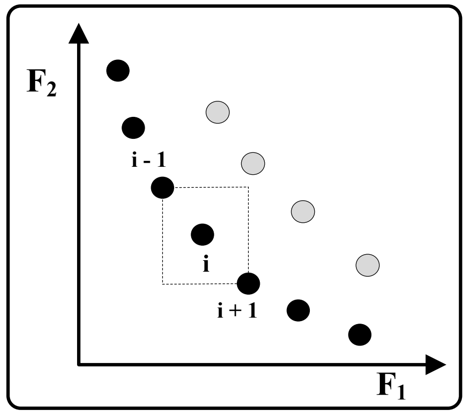


Fig. 4-4 Crowding distance measurement

Although the crowding distance (diversity) is calculated in objective function space, if required, it can also be implemented in the design variable space [44].

4.4 MULTI-OBJECTIVE PROBLEM FORMUALTION OF NOVA PARALLEL HYBRID ELECTRIC TRANSIT BUS

Mathematical formulation for the optimal selection of parameters of the NOVA parallel hybrid electric transit bus is shown in equations 4-1 to 4-6. The problem consists of an objective function, i.e. achieving best fuel economy with least emissions, as shown in equations 4-1 to 4-4, with three drivetrain and five control strategy variables, with their respective upper and lower bounds, as shown in equation 4-5. In equation 4-5, fc_trq_scale, mc_trq_scale, and ess_cap_scale are the scaled factors that decide the ICE, motor/controller, and ESS size, respectively. The default values of ICE power, motor/controller torque, and ESS capacity are multiplied with scaled values, to obtain current ICE power, EM power, and ESS capacity. The values of bus performance constraints (acceleration and gradeablity) are shown in equations 4-6 and 4-7, respectively. Parameters of the multi-objective optimization algorithm are listed in Table 4-6.

Table 4-6 Multi-objectives genetic algorithm parameters

No	Parameter	Value
1	Population size	25
2	Generation	100
3	Crossover probability	0.8
4	Mutation probability	0.1

(i) Multi-objective function parameter:

F1(X)= Fuel Economy (4-1)

F2(X)= NO_X Emissions (4-2)

F3(X)= CO Emissions (4-3)

F4(X)= HC Emissions (4-4)

(ii) Fitness function parameters:

$$\left.\begin{array}{l}X=[fc\_trq\_scale,\ mc\_trq\_scale,\ ess\_cap\_scale,\\ \quad cs\_off\_trq\_fac,\ cs\_min\_trq\_fac, cs\_charge\_trq,\\ \quad cs\_electric\_launch\_spd\_lo, cs\_electric\_launch\_spd\_hi]\\ \ x1\rightarrow[0.56,1],\ \ x2\rightarrow[0.66,2],\ x3\rightarrow[0.2,3],\ x4\rightarrow[0,1]\\ \ x5\rightarrow[0,1],\ x6\rightarrow[0,30],\ x7\rightarrow[0,10],\ x8\rightarrow[11,30]\end{array}\right\} \qquad (4\text{-}5)$$

(iii) Constraint parameters:

Acceleration time (0-80 km/h) < 50 sec (4-6)

Gradeability (@16 km/h for 20 sec) > 10 % (4-7)

4.5 LINKING OF ADVISOR AND NSGA-II

Since ADVISOR can also run in batch mode, without GUI, it is possible to integrate ADVISOR with other programs. In this study NSGA-II is written in MATLAB. However, the objective and constraint functions are evaluated in ADVISOR, within the MATLAB environment. NSGA-II alters the value of the fitness function parameters, listed equation 4-5, and evaluates them on complete simulation tests, such as the drive cycle test, acceleration test, and gradeability test.

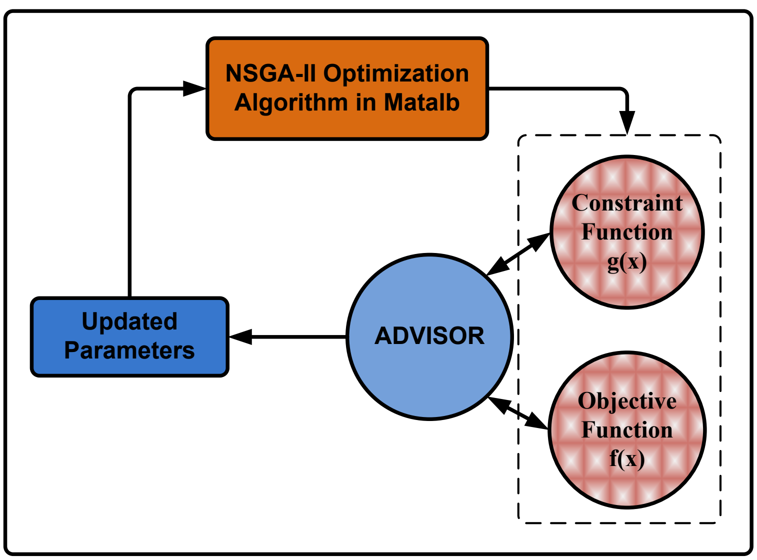


Fig. 4-5 Linking of ADVISOR and NSGA-II optimization algorithm

The drive cycle test is used to evaluate the multi-objective function parameters, i.e., fuel economy and emissions, where as acceleration and gradeabilty tests are used for evaluating constraint functions. Fig. 4-5 illustrates the integration of NSGA-II optimization algorithm and the ADVISOR software.

4.6 SIMULATION AND PERFORMANCE ANALYSIS

Fuel economy and emissions are highly influenced by the acceleration rate, number of stops, and idle time. As such, the drive cycle has a considerable effect on measured fuel economy and emissions. Since there is no definitive cycle for testing heavy-duty transit vehicles, this thesis uses three different drive cycles with varying average speeds and number of stops per kilometre. At this stage, the multi-objective and constraint function parameters, based on the NSGA-II optimization algorithm, are evaluated on the standard Urban Dynamometer Driving Schedule (UDDS), Montreal Pie-IX 139 drive cycle, and New York bus driving patterns, respectively under standard ambient conditions. The initial ambient temperature of the ICE parts, exhaust system catalyst, and the motor is 20°C. Two different control strategies are used. The drive cycles and control strategies are modeled in ADVISOR and are used for test purposes in this study.

4.6.1 UDDS DRIVE CYCLE

The cycle simulates an urban route of 11.99 km, with 17 stops. The maximum and the average speeds are 91.25 km/h and 31.51km/h, respectively. The average acceleration is 0.5 m/sec^2. Total cycle time and idle time are 1369 seconds and 259 seconds, respectively. The drive cycle is shown in Fig. 4-6.

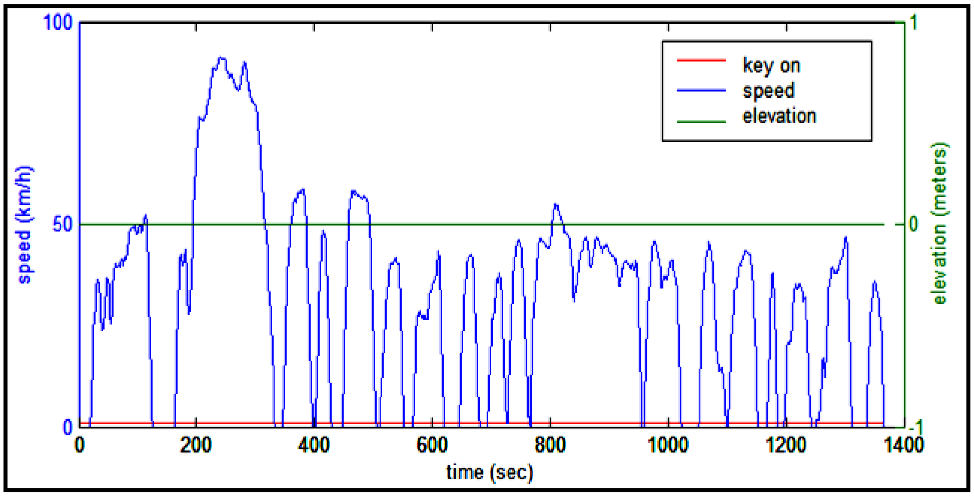


Fig. 4-6 Urban dynamometer driving schedule (UDDS)

4.6.2 MONTREAL 139 PIE-IX DRIVE CYCLE

The cycle simulates the Montreal city transit bus route of STM 139. Total distance of the route is 8.32 km, with 22 stops and high acceleration. The maximum and average speeds are 58.58 km/h and 21.14 km/h, respectively. The average acceleration is 0.72 m/sec^2. Total cycle time and idle time are 1416 seconds and 453 seconds, respectively. The drive cycle is shown in Fig. 4-7.

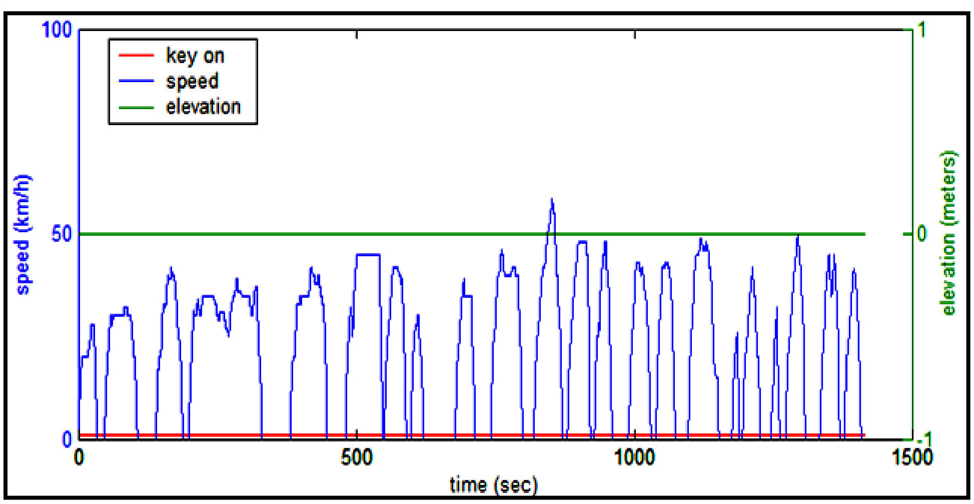


Fig.4-7 Montreal Pie-IX 139 drive cycle

4.6.3 New York Bus Drive Cycle

The New York Bus (NY Bus) cycle is a chassis dynamometer test for heavy-duty transit vehicles, particularly for urban buses. The NY Bus cycle is representative of actual observed driving patterns of transit buses in New York city. It is a short test cycle with 11 numbers of stops, fast average acceleration, and low speed. Total distance of the cycle is 0.99 km. The maximum and average speeds are 49.57 km/h and 5.93 km/h, respectively. The average acceleration is 1.17 m/sec^2. Total cycle time and idle time are 600 seconds and 404 seconds, respectively. The drive cycle is illustrated in Fig. 4-8.

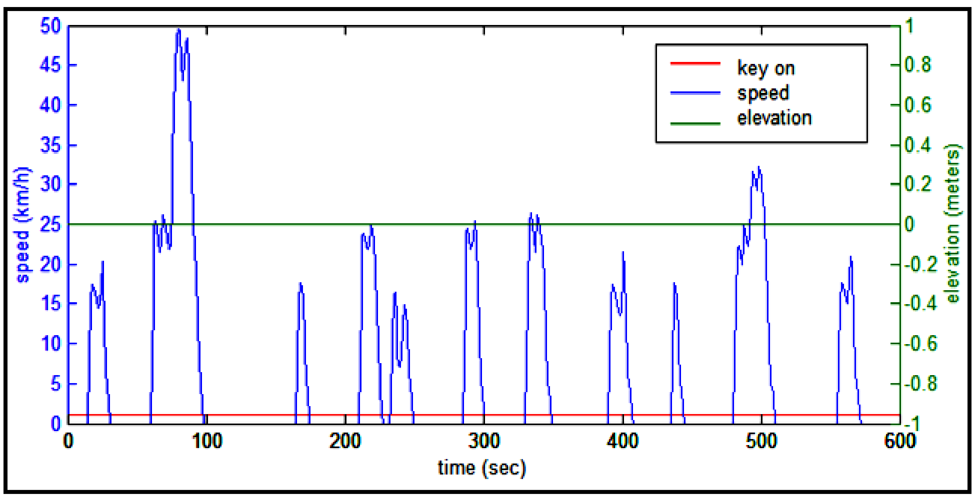


Fig. 4-8 New York bus drive cycle

The population size of solutions was set to 25, and the total number of generations was set to 100. After 2526 ADVISOR runs on an Intel Core-II duo processor (2.66 GHz), final trade-off solutions were obtained for four objectives and eight variables listed in equations 4-1 to 4-5, respectively. Obtained trade-off solutions for objectives and design variables for three drive cycles, using two control strategies, are tabulated in Tables 4-7, 4-8, 4-9, 4-10, 4-11, and 4-12, respectively.

Table 4-7 Trade-off solutions: UDDS drive cycle-electric assist control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
60.59	24.34	5.72	0.50	45.97	13.92	120.88	84.23	72.49	0.73	0.73	20.37	1.81	5.09
60.16	24.23	0.31	0.52	48.76	13.92	123.43	76.36	65.46	0.69	0.65	28.52	2.09	3.43
66.18	27.45	6.42	0.52	35.82	13.92	138.84	149.19	132.86	0.05	0.14	21.41	1.60	4.91
60.45	24.32	0.31	0.52	47.15	13.92	122.94	80.10	65.08	0.78	0.67	27.63	1.90	4.48
66.23	27.44	6.42	0.52	35.82	13.92	138.84	148.99	132.86	0.05	0.08	22.12	1.60	4.67
63.03	25.43	0.28	0.51	40.51	13.92	130.88	100.49	70.63	0.73	0.59	27.13	2.03	3.00
68.81	26.60	0.31	0.55	36.74	13.92	147.51	148.60	76.86	0.98	0.96	4.40	2.59	3.74
64.28	25.36	0.28	0.51	39.03	13.92	133.86	118.63	73.18	0.89	0.77	15.04	1.69	4.03
66.60	27.86	6.43	0.52	36.32	13.92	140.84	148.95	99.96	0.29	0.17	11.53	2.32	4.10
70.20	27.22	6.66	0.54	34.58	13.92	149.59	140.60	158.57	0.22	0.77	9.54	1.39	3.25
61.73	25.35	6.05	0.48	38.52	13.92	124.95	113.52	123.02	0.61	0.41	23.74	1.74	3.09
60.73	24.34	0.32	0.50	49.14	13.92	123.43	76.36	80.46	0.69	0.90	28.52	1.06	3.84
66.27	27.42	6.42	0.52	35.82	13.92	138.84	149.19	132.86	0.05	0.14	22.41	2.60	5.41
67.08	26.95	6.29	0.53	36.61	13.92	136.86	147.94	105.21	0.34	0.51	18.06	2.42	4.67
68.43	26.92	6.44	0.53	36.26	13.92	147.17	148.76	84.54	0.20	0.71	8.07	2.60	4.75
69.46	26.98	0.52	0.58	34.63	13.92	149.03	140.41	156.73	0.31	0.73	13.77	1.42	3.37
60.25	24.23	5.79	0.50	48.76	13.92	123.43	76.36	65.46	0.69	0.65	29.52	2.09	3.43
66.31	28.08	6.57	0.52	34.80	13.92	147.55	147.09	140.23	0.16	0.26	10.60	1.48	3.68
61.78	24.48	5.80	0.50	40.95	13.92	120.88	121.73	72.49	0.98	0.73	19.37	1.81	4.09
68.36	26.49	6.46	0.53	36.11	13.92	139.51	148.61	111.54	0.30	0.72	6.26	1.75	3.90
64.29	27.30	6.43	0.54	38.21	13.92	140.74	101.67	90.45	0.38	0.20	21.44	2.23	4.36
66.29	26.15	0.29	0.54	38.71	13.92	142.34	106.56	68.38	0.74	0.86	20.23	2.11	3.36
65.52	26.65	0.32	0.50	38.83	13.92	135.30	142.46	70.97	0.30	0.34	24.96	2.09	4.56
68.81	26.60	0.31	0.55	36.74	13.92	147.51	148.60	76.86	0.98	0.96	4.40	1.09	4.74
66.18	27.45	6.42	0.52	35.82	13.92	138.84	149.19	132.86	0.05	0.14	21.41	1.60	4.91

Table 4-8 Trade-off solutions: MTL-139 Pie-IX drive cycle-electric assist control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
62.85	25.77	0.72	0.52	41.27	13.92	108.58	138.24	88.51	0.90	0.07	0.17	1.40	3.42
62.58	25.89	0.72	0.52	41.20	13.92	108.59	138.24	89.54	0.91	0.01	0.24	1.40	3.48
61.57	23.72	0.88	0.58	35.01	13.92	145.03	144.14	160.67	0.15	0.70	11.32	1.82	3.79
54.91	22.06	0.71	0.55	37.58	13.92	132.44	137.30	160.01	0.69	0.62	6.59	1.79	3.77
61.07	22.82	0.76	0.55	35.49	13.92	141.82	143.83	135.14	0.71	0.84	7.60	2.66	4.71
62.85	25.77	0.72	0.52	41.27	13.92	108.58	138.24	88.51	0.90	0.07	0.17	1.40	2.92
55.12	20.71	0.57	0.53	37.70	13.92	128.60	143.75	167.49	0.85	0.84	9.60	1.70	3.29
54.96	22.11	0.71	0.55	37.56	13.92	132.63	137.35	160.01	0.69	0.62	6.59	1.79	3.77
61.45	23.24	0.82	0.57	35.16	13.92	143.42	144.78	160.61	0.39	0.77	10.76	2.25	4.05
62.59	23.83	0.89	0.58	34.90	13.92	146.33	141.96	153.91	0.31	0.73	12.43	2.33	4.12
59.22	22.08	0.67	0.53	35.85	13.92	137.14	143.88	160.64	0.70	0.84	13.81	2.46	4.58
63.14	25.82	0.84	0.52	40.26	13.92	109.60	146.36	103.84	0.81	0.07	2.66	1.45	3.61
62.85	25.77	0.72	0.52	41.27	13.92	108.58	138.24	88.51	0.90	0.07	0.17	1.40	2.92
58.20	21.72	0.63	0.53	37.47	13.92	135.18	146.59	174.28	0.46	0.93	9.81	2.16	3.99
62.54	25.92	0.73	0.52	41.15	13.92	108.88	138.58	89.63	0.93	0.01	0.25	1.41	3.49
62.85	25.77	0.72	0.52	41.27	13.92	108.58	138.24	88.48	0.90	0.07	0.17	1.40	3.08
60.29	23.35	0.82	0.57	35.40	13.92	141.98	139.49	149.60	0.59	0.68	15.06	2.10	3.95
55.52	21.49	0.65	0.55	36.54	13.92	131.47	141.60	150.45	0.80	0.70	8.61	1.61	3.06
62.73	23.46	0.84	0.57	34.91	13.92	145.81	144.25	162.05	0.44	0.84	12.49	2.04	4.78
61.85	23.06	0.81	0.56	35.22	13.92	143.63	141.47	147.58	0.40	0.89	16.99	2.26	3.99
59.94	22.38	0.71	0.54	35.74	13.92	138.93	138.66	151.20	0.63	0.84	14.91	2.24	3.79
75.64	28.88	1.28	0.62	34.49	13.92	149.78	148.72	168.20	0.76	0.70	11.58	1.88	3.54
62.01	23.13	0.80	0.56	35.19	13.92	144.07	139.50	145.43	0.26	0.86	17.36	2.35	3.98
63.30	23.53	0.85	0.57	34.87	13.92	146.24	144.30	162.20	0.71	0.84	13.34	2.66	4.89
62.72	25.84	0.82	0.52	40.65	13.92	109.97	144.26	94.42	0.81	0.11	1.21	1.48	3.57

Table 4-9 Trade-off solutions: New York bus drive cycle-electric assist control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
88.42	44.95	41.41	1.95	42.64	13.92	109.22	109.17	79.72	0.77	0.27	17.23	1.19	4.32
120.26	53.31	43.12	2.95	35.76	13.92	141.13	140.63	121.18	0.02	0.66	10.02	2.59	4.91
94.50	38.44	26.53	2.27	39.38	13.92	108.53	149.23	150.90	0.78	0.75	19.47	1.74	3.11
84.86	52.30	55.72	1.84	40.47	13.92	112.44	130.73	93.12	0.68	0.01	0.01	1.43	3.51
116.47	55.37	46.57	2.88	35.90	13.92	140.48	126.68	138.64	0.78	0.54	29.58	1.00	4.22
84.66	52.46	56.00	1.84	40.47	13.92	112.44	130.73	93.12	0.93	0.00	0.15	1.43	3.51
104.20	51.78	46.20	2.34	37.13	13.92	127.36	146.90	134.06	0.57	0.38	15.85	2.31	5.50
102.24	49.41	40.39	2.46	38.88	13.92	122.35	133.75	95.33	0.40	0.46	3.53	1.98	3.33
115.03	53.16	44.22	2.73	36.30	13.92	135.04	145.68	128.05	0.17	0.52	13.57	2.52	5.26
95.42	45.26	36.26	2.20	38.95	13.92	112.93	139.96	141.71	0.14	0.40	15.74	2.79	3.38
119.39	55.49	46.40	2.96	35.54	13.92	142.67	137.89	125.56	0.23	0.57	18.05	1.78	4.56
87.56	46.92	46.97	1.78	39.84	13.92	110.08	134.43	117.28	0.91	0.14	13.21	1.71	3.29
111.45	61.10	58.50	2.42	36.56	13.92	142.69	136.67	88.93	0.76	0.32	21.88	1.16	4.31
89.10	52.61	54.13	1.84	39.61	13.92	115.56	128.74	103.32	0.86	0.09	7.37	1.36	3.56
119.45	55.45	46.65	2.90	35.61	13.92	142.70	127.73	139.00	0.80	0.55	29.60	1.01	4.22
100.34	51.53	47.76	2.21	38.54	13.92	125.38	115.05	111.92	0.49	0.31	20.89	1.36	4.36
91.00	45.60	40.07	2.05	41.59	13.92	111.53	121.44	81.86	0.50	0.32	14.25	1.53	4.07
103.99	48.17	38.76	2.39	38.14	13.92	121.91	129.43	128.49	0.81	0.45	28.26	1.50	3.81
93.26	53.82	54.07	1.89	38.29	13.92	119.31	138.98	128.58	0.59	0.13	8.56	1.91	4.98
102.04	52.73	48.82	2.33	38.18	13.92	127.58	133.48	95.55	0.50	0.37	5.39	1.80	3.94
105.68	64.64	65.06	2.27	35.49	13.92	141.98	141.59	133.35	0.32	0.18	12.57	1.42	3.80
127.65	53.44	43.19	3.00	34.98	13.92	146.19	149.83	135.31	0.04	1.00	15.65	1.39	5.35
130.18	54.75	45.03	3.07	34.63	13.92	149.58	149.83	134.99	0.03	0.88	15.65	2.07	5.36
84.64	52.46	56.01	1.84	40.49	13.92	112.44	129.77	93.12	0.93	0.00	0.14	1.45	3.52
124.77	53.05	42.44	4.79	35.19	13.92	143.40	143.70	155.81	0.48	0.68	25.72	1.84	4.41

Table 4-10 Trade-off solutions: UDDS drive cycle-fuzzy logic control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
59.58	25.37	5.90	0.50	43.79	13.92	121.97	90.46	89.71	0.46	0.31	1.40	2.12	3.41
62.09	25.86	0.35	0.52	38.86	13.92	132.42	119.44	77.44	0.52	0.07	24.88	2.05	3.88
65.10	25.87	0.28	0.55	40.19	13.92	126.10	136.90	70.56	0.68	0.63	21.65	1.84	4.11
60.36	24.89	5.87	0.48	45.29	13.92	126.56	84.27	87.15	0.52	0.15	27.49	1.20	3.22
67.32	26.93	6.50	0.54	35.91	13.92	142.13	122.11	133.17	0.91	0.58	28.18	1.16	3.82
69.18	26.66	6.46	0.53	34.88	13.92	147.04	137.86	150.66	0.99	0.75	23.74	2.22	3.61
68.12	27.16	6.64	0.53	34.63	13.92	148.37	148.00	160.12	0.88	0.58	20.59	2.17	4.98
65.60	28.05	6.59	0.53	36.13	13.92	148.74	112.91	96.85	0.15	0.24	13.42	2.28	3.30
61.56	24.89	0.30	0.50	49.07	13.92	115.67	82.31	91.84	0.65	0.59	26.68	1.59	3.96
67.72	27.05	6.54	0.53	34.97	13.92	147.73	130.57	144.46	0.91	0.58	23.63	1.38	4.70
67.83	27.80	6.51	0.52	35.42	13.92	142.96	148.64	127.54	0.23	0.40	12.52	2.56	3.98
68.82	28.40	6.75	0.54	34.53	13.92	149.42	147.05	166.47	0.18	0.46	4.48	2.01	5.09
64.06	25.62	6.13	0.53	37.39	13.92	133.71	121.12	103.98	0.77	0.67	17.38	2.59	3.64
61.55	25.54	6.06	0.50	39.89	13.92	122.42	109.98	123.68	0.47	0.42	2.63	1.51	3.79
67.70	26.58	6.47	0.53	35.39	13.92	147.88	126.86	112.12	0.76	0.85	21.52	2.23	4.79
66.82	27.52	6.51	0.52	35.00	13.92	146.02	142.43	139.14	0.32	0.36	20.04	2.33	4.03
65.48	27.31	0.33	0.54	36.44	13.92	149.69	112.17	85.56	0.70	0.25	26.26	2.23	2.99
65.79	25.77	6.13	0.49	37.11	13.92	129.59	134.20	125.96	0.93	0.75	19.01	2.79	4.38
63.13	26.73	6.19	0.53	37.64	13.92	134.72	121.03	93.00	0.60	0.30	7.65	2.05	3.64
67.39	28.64	6.67	0.53	34.99	13.92	149.58	135.21	115.37	0.41	0.28	6.10	2.12	3.08
63.98	26.15	0.34	0.51	39.71	13.92	128.95	134.03	71.10	0.55	0.33	22.99	1.95	3.98
68.68	26.84	6.54	0.54	35.27	13.92	145.05	129.51	148.03	0.95	0.70	28.16	1.18	3.69
67.71	27.85	6.57	0.53	34.93	13.92	145.95	148.26	146.76	0.19	0.45	9.22	2.35	4.22
67.93	27.28	6.54	0.53	35.35	13.92	143.81	142.58	127.79	0.83	0.53	21.50	2.48	3.62
66.13	27.43	0.37	0.54	36.38	13.92	149.69	116.86	83.21	0.68	0.22	26.25	2.20	3.03

Table 4-11 Trade-off solutions MTL-139 drive cycle-fuzzy logic control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
61.13	22.80	0.76	0.55	35.38	13.92	141.50	143.17	159.86	0.87	0.87	2.92	1.96	4.52
59.28	22.68	0.73	0.55	35.67	13.92	138.79	144.80	160.47	0.74	0.69	21.15	1.48	4.79
55.39	21.03	0.59	0.54	38.26	13.92	129.84	126.05	155.47	0.85	0.77	3.37	1.88	4.39
55.62	20.95	0.59	0.54	36.83	13.92	130.21	134.67	145.96	0.61	0.91	7.21	1.57	4.03
63.66	23.63	0.87	0.57	34.78	13.92	146.97	146.02	163.35	0.87	0.93	9.82	2.29	4.65
60.43	23.09	0.79	0.57	35.37	13.92	141.43	145.88	160.69	0.85	0.71	17.67	2.74	4.15
61.32	23.09	0.80	0.57	35.24	13.92	142.64	146.80	163.22	0.89	0.80	18.78	2.68	4.66
62.45	23.20	0.82	0.56	35.05	13.92	144.15	148.28	164.74	0.89	0.98	19.82	2.13	3.67
55.37	20.88	0.58	0.53	38.31	13.92	129.57	115.88	153.64	0.76	0.88	7.22	1.53	3.30
64.94	24.08	0.95	0.58	34.48	13.92	149.74	149.93	163.69	0.68	0.96	21.88	2.14	4.82
58.16	21.71	0.63	0.53	37.51	13.92	135.16	134.39	175.45	0.39	0.95	15.23	1.65	4.47
59.65	22.26	0.70	0.54	35.82	13.92	138.27	138.26	150.35	0.42	0.90	12.87	1.56	4.91
63.95	23.83	0.89	0.58	34.71	13.92	147.65	146.95	164.55	0.82	0.83	20.52	2.43	4.67
59.67	22.76	0.75	0.56	35.64	13.92	139.41	141.19	155.14	0.89	0.72	11.78	2.73	4.35
59.01	22.04	0.67	0.53	37.11	13.92	137.11	146.03	166.12	0.68	0.97	19.51	1.70	3.98
59.97	22.68	0.74	0.56	35.60	13.92	139.52	143.54	155.83	0.93	0.76	8.46	2.22	4.98
64.89	24.06	0.94	0.58	34.51	13.92	149.65	147.36	165.98	0.37	0.90	22.74	1.93	4.67
58.72	21.92	0.66	0.53	37.21	13.92	136.44	131.24	177.50	0.19	0.90	17.11	1.31	4.27
64.91	24.07	0.95	0.58	34.50	13.92	149.69	147.65	164.47	0.54	0.94	22.06	2.04	4.69
58.72	21.92	0.66	0.53	37.21	13.92	136.44	131.24	177.50	0.19	0.90	17.11	1.31	4.27
64.45	24.09	0.94	0.58	34.52	13.92	149.65	147.36	159.42	1.00	0.84	22.58	2.12	4.71
62.87	23.47	0.85	0.58	34.94	13.92	145.25	148.47	163.30	0.89	0.81	21.06	2.64	4.72
62.40	23.24	0.83	0.56	35.03	13.92	144.64	147.41	155.10	0.90	0.85	16.08	2.07	5.13
63.16	23.50	0.86	0.57	34.88	13.92	146.29	144.00	154.58	0.64	0.99	7.27	1.53	4.17
56.62	21.35	0.63	0.55	36.45	13.92	132.58	139.74	149.05	0.84	0.85	8.00	1.76	5.38

Table 4-12 Trade-off solutions New York Bus drive cycle-fuzzy logic control

Objectives				Constraints		Drivetrain Parameters			Control Strategy Parameters				
FE L/100 km	NO_X g/km	HC g/km	CO g/km	Accel. sec	Grade %	X1 kW	X2 kW	X3 Ah	X4	X5	X6	X7	X8
88.42	44.95	41.41	1.95	42.64	13.92	109.22	109.17	79.72	0.77	0.27	17.23	1.19	4.32
120.26	53.31	43.12	2.95	35.76	13.92	141.13	140.63	121.18	0.02	0.66	10.02	2.59	4.91
94.50	38.44	26.53	2.27	39.38	13.92	108.53	149.23	150.90	0.78	0.75	19.47	1.74	3.11
84.86	52.30	55.72	1.84	40.47	13.92	112.44	130.73	93.12	0.68	0.01	0.01	1.43	3.51
116.47	55.37	46.57	2.88	35.90	13.92	140.48	126.68	138.64	0.78	0.54	29.58	1.00	4.22
84.66	52.46	56.00	1.84	40.47	13.92	112.44	130.73	93.12	0.93	0.00	0.15	1.43	3.51
104.20	51.78	46.20	2.34	37.13	13.92	127.36	146.90	134.06	0.57	0.38	15.85	2.31	5.50
102.24	49.41	40.39	2.46	38.88	13.92	122.35	133.75	95.33	0.40	0.46	3.53	1.98	3.33
115.03	53.16	44.22	2.73	36.30	13.92	135.04	145.68	128.05	0.17	0.52	13.57	2.52	5.26
95.42	45.26	36.26	2.20	38.95	13.92	112.93	139.96	141.71	0.14	0.40	15.74	2.79	3.38
119.39	55.49	46.40	2.96	35.54	13.92	142.67	137.89	125.56	0.23	0.57	18.05	1.78	4.56
87.56	46.92	46.97	1.78	39.84	13.92	110.08	134.43	117.28	0.91	0.14	13.21	1.71	3.29
111.45	61.10	58.50	2.42	36.56	13.92	142.69	136.67	88.93	0.76	0.32	21.88	1.16	4.31
89.10	52.61	54.13	1.84	39.61	13.92	115.56	128.74	103.32	0.86	0.09	7.37	1.36	3.56
119.45	55.45	46.65	2.90	35.61	13.92	142.70	127.73	139.00	0.80	0.55	29.60	1.01	4.22
100.34	51.53	47.76	2.21	38.54	13.92	125.38	115.05	111.92	0.49	0.31	20.89	1.36	4.36
91.00	45.60	40.07	2.05	41.59	13.92	111.53	121.44	81.86	0.50	0.32	14.25	1.53	4.07
103.99	48.17	38.76	2.39	38.14	13.92	121.91	129.43	128.49	0.81	0.45	28.26	1.50	3.81
93.26	53.82	54.07	1.89	38.29	13.92	119.31	138.98	128.58	0.59	0.13	8.56	1.91	4.98
102.04	52.73	48.82	2.33	38.18	13.92	127.58	133.48	95.55	0.50	0.37	5.39	1.80	3.94
105.68	64.64	65.06	2.27	35.49	13.92	141.98	141.59	133.35	0.32	0.18	12.57	1.42	3.80
127.65	53.44	43.19	3.00	34.98	13.92	146.19	149.83	135.31	0.04	1.00	15.65	1.39	5.35
130.18	54.75	45.03	3.07	34.63	13.92	149.58	149.83	134.99	0.03	0.88	15.65	2.07	5.36
84.64	52.46	56.01	1.84	40.49	13.92	112.44	129.77	93.12	0.93	0.00	0.14	1.45	3.52
124.77	53.05	42.44	2.98	35.19	13.92	143.40	143.70	155.81	0.48	0.68	25.72	1.84	4.41

In multi-objective optimization, when the number of objective functions is more than two, performance illustration of algorithm becomes difficult using two-dimensional objective space plot. In order to present the pair wise interaction among the solutions of four objectives, $\binom{4}{2}$ or 4 *3 =12 scatter plot interactions are plotted as shown in Figs. 4-9, 4-10, 4-11, 4-12, 4-13, and 4-14 respectively, for three drives cycles and two control strategies. In all interactive plots, the diagonal sub-plots mark the axis for the corresponding off-diagonal sub-plots. For example, the subplot in position (1, 2) has its horizontal axis marked with NO_X emission, [F (2)], and the vertical axis marked with fuel economy, [F (1)]. The designer has the flexibility in viewing the plots. If the designer is not comfortable in viewing a plot with NO_X emission on the horizontal axis, the sub-plot in position (2, 1) shows the same plot with NO_X emission marked in the vertical axis. Thus, a plot in the position (i, j) of the matrix is identical to the plot in the position (j, i), except that the plot is mirrored.

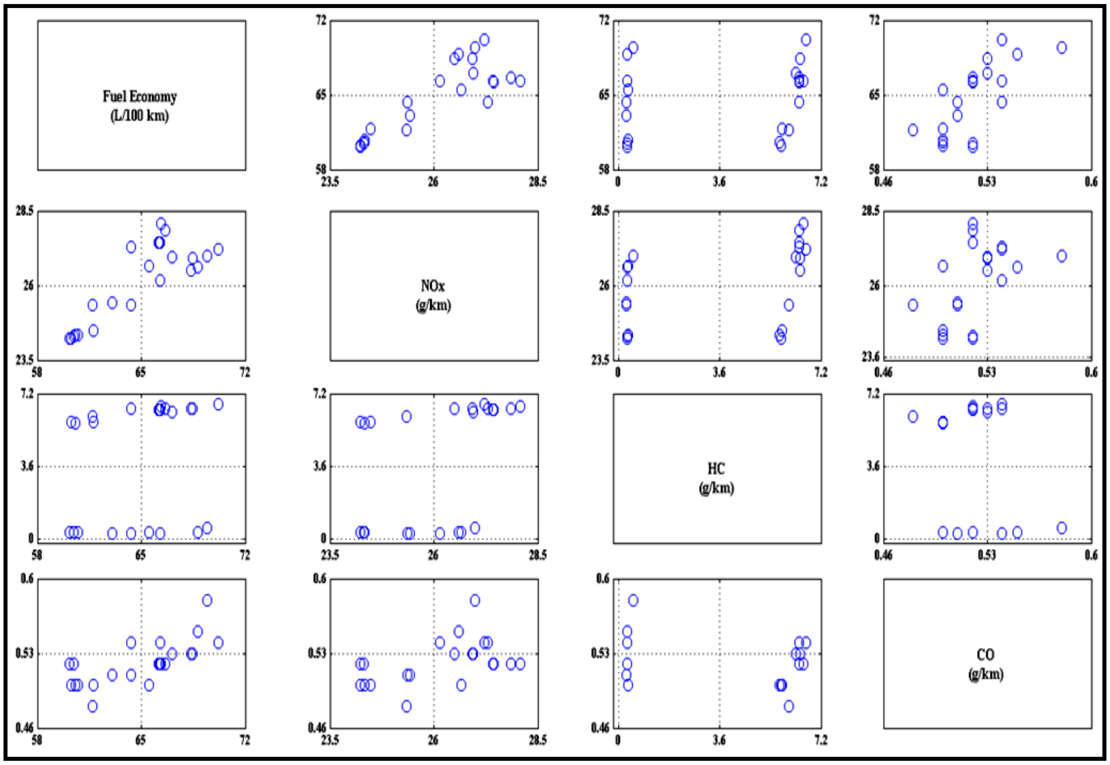


Fig. 4-9 Objective Trade-off: UDDS drive cycle-electric assist control

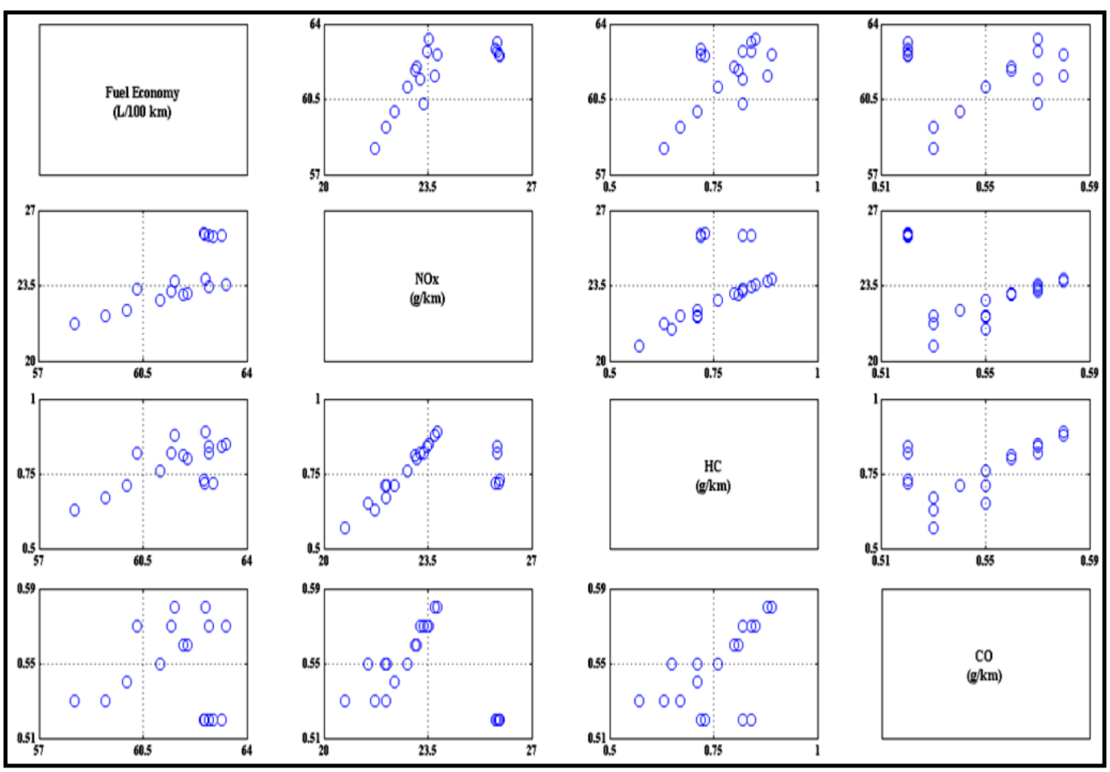


Fig. 4-10 Objective Trade-off: MTL-139 Pie-IX bus drive cycle-electric assist control

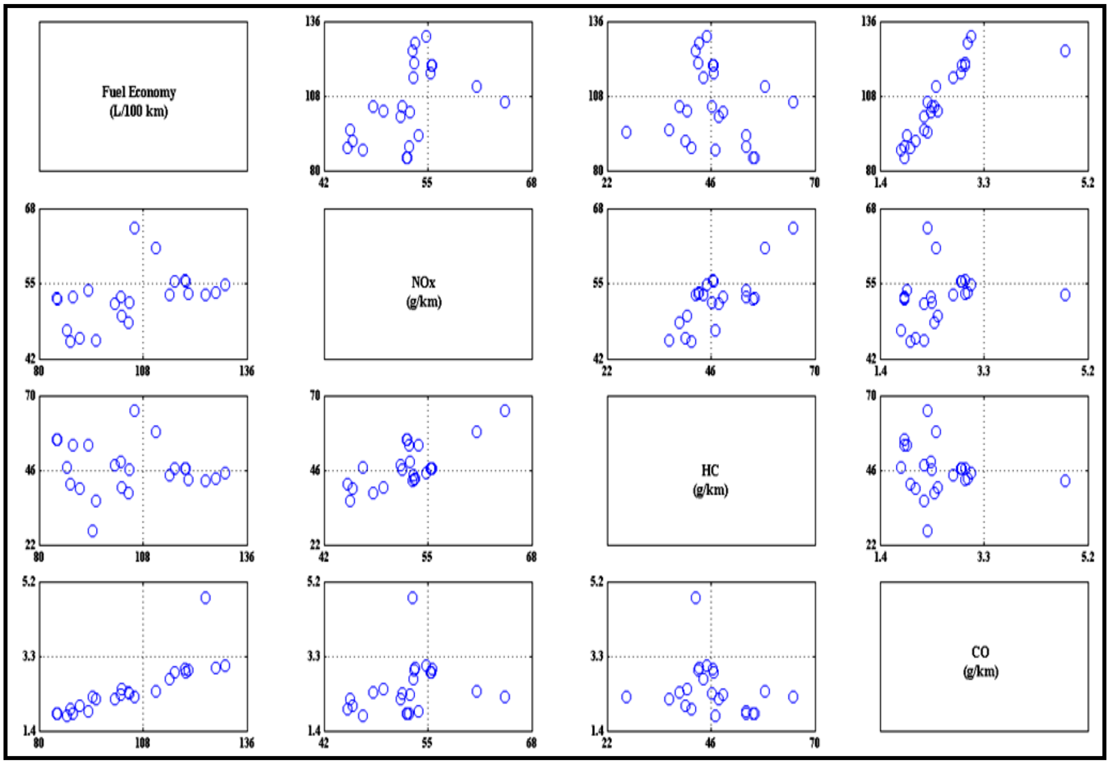


Fig. 4-11 Objective Trade-off: New York bus drive cycle-electric assist control

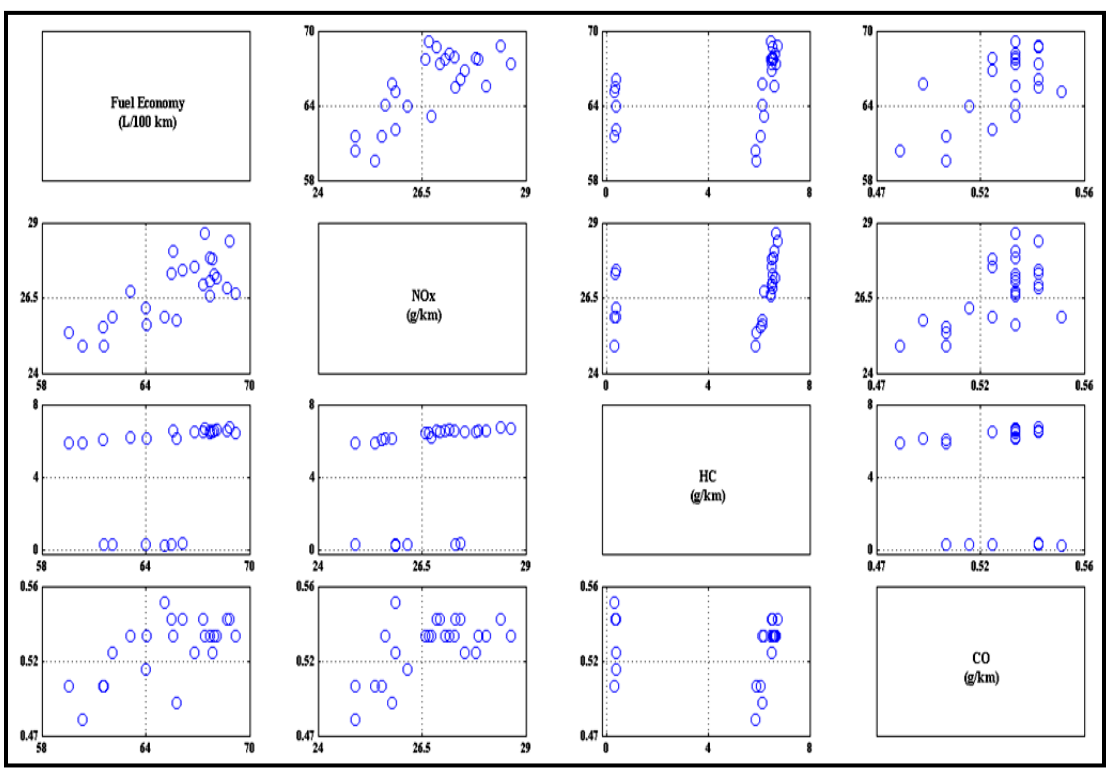


Fig. 4-12 Objective Trade-off: UDDS drive cycle-fuzzy logic control

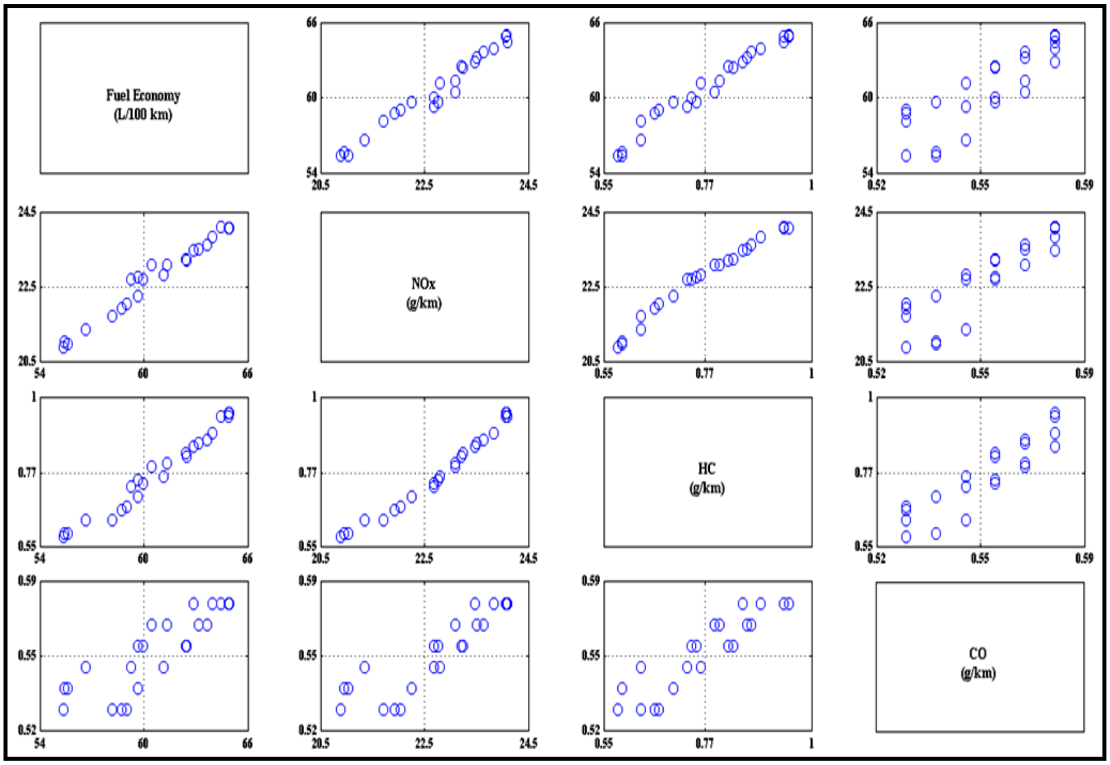


Fig.4-13 Objective Trade-off: MTL-139 Pie-IX bus drive cycle-fuzzy logic control

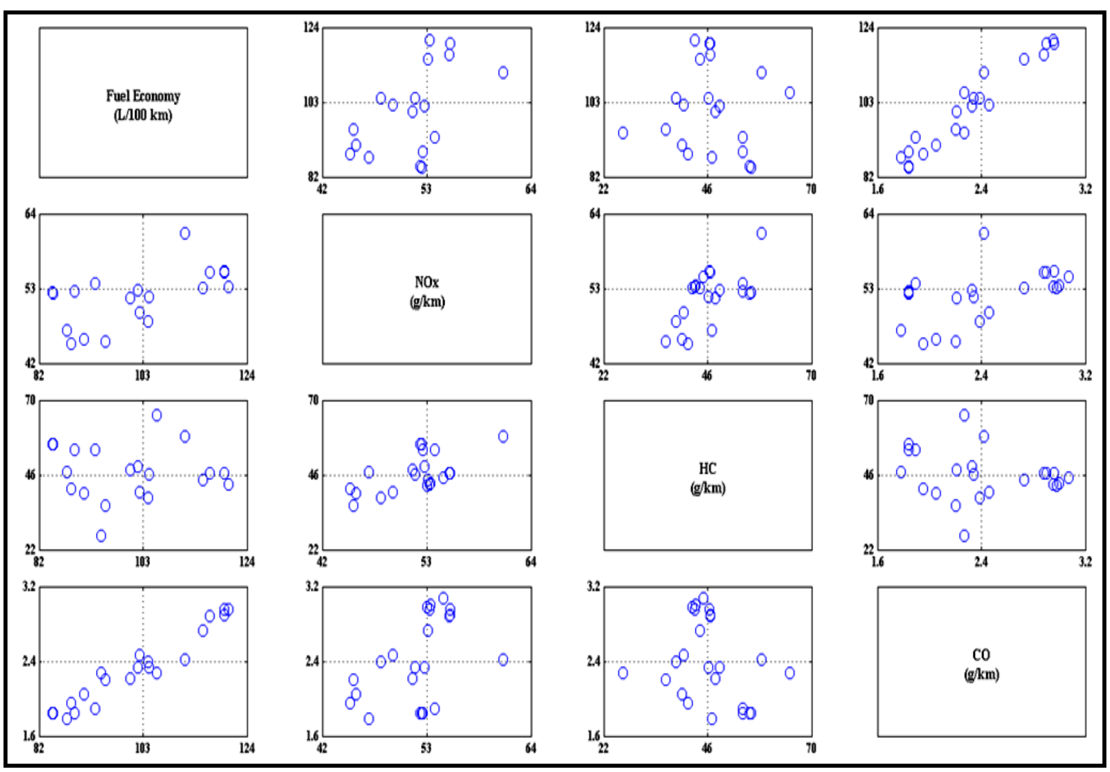


Fig. 4-14 Objective Trade-off: New York Bus drive cycle-fuzzy logic control

In order to evaluate the effectiveness of the NSGA-II algorithm, and to validate the optimal results, a comparison is performed between conventional bus parameters and the parameters of the NOVA parallel hybrid electric transit bus, obtained after optimization in ADVISOR. The performance parameters obtained after evaluating traditional NOVA transit bus configuration on UDDS, Montreal Pie-IX 139, and New York Bus drive cycles are listed Table 4-13.

Table 4-13 Traditional *Nova* transit bus performance parameters

	UDDS Drive Cycle	Montreal Pie- IX 139 Drive Cycle	New York Bus Drive Cycle
Fuel Economy (L/100 km)	**69.5**	**79**	**243.8**
NO_X (g/km)	**53.93**	**82.47**	**406.97**
HC (g/km)	**2.65**	**4.569**	**37.76**
CO (g/km)	**0.393**	**0.709**	**2.75**

It is clear from the data of Tables 4-7 to 4-12 that post-optimization, the values of all four objectives, i.e., fuel economy and emissions, obtained on all three drive cycles, are improved, compared to those of the traditional ones. Furthermore, the obtained 25 solutions satisfy vehicle performance constraints, listed in Table 4-3. Though this comparison cannot sufficiently demonstrate that the solutions are real trade-offs, it does demonstrate that the obtained solutions are at least better than the traditional ones. The obtained results show substantial reduction in ICE power rating and emissions, due to the presence of the electric motor. After optimization, it is clear that fuel economy and overall efficiency of the drivetrain increases. This is because the developed control strategy forces the ICE to operate closer to its most efficient operating region. A detailed analytical comparison is shown in next section. The range of each objective and design variable is listed in Table 4-14. In addition, from Figs. 4-9 and 4-12, for the UDDS drive cycle, it is observed that there exists a wide range of discrepancy in HC emissions, compared to other drive cycles. This is because the average speed of the engine under UDDS drive cycle is much higher than the other two drive cycles. Furthermore, the engine idle time for the UDDS drive cycle is much lower compared to other drive cycles. Hence, the engine depicts higher discrepancy in the column representing trade-off for HC emissions, in Figs. 4-9 and 4-12.

For better visualization and comparison of obtained multiple trade-off solutions, the objectives and the design variables of Tables 4-7 to 4-12 are represented using the star-coordinate system, suggested by Manas [45].

In the star coordinate method, for N objective functions, a circle is divided into N equal arcs. Each radial line, connecting the end of an arc with the center of the circle, represents the axis for each objective function. For each line, the center of the circle and circumference marks the minimum and maximum value of the objective function. Since each objective function has a different range, the axes are scaled corresponding to the range of the objective. Figs. 4-15 to 4-20 represent comparative scenarios of obtained solutions in objective and design variable space, using the start-coordinate system. In each figure the right hand side plot shows design variables, whereas the left hand side plot represents the objectives.

Table 4-14 Objectives and range of design variables

	Electric Assist Control			Fuzzy Logic Control		
	UDDS Drive Cycle	**Montreal Pie- IX 139**	**NY Bus Drive Cycle**	**UDDS Drive Cycle**	**Montreal Pie- IX 139**	**NY Bus Drive Cycle**
Fuel Economy (L/100 km)	60.16-70.20	54.91-75.64	84.64-130.18	59.58-69.18	55.37-64.94	84.64-130.18
NOX (g/km)	24.23-28.08	20.71-28.88	38.44-64.64	24.89-28.64	20.88-24.09	38.44-64.64
HC (g/km)	0.28-6.66	0.57-1.28	26.53-65.06	0.28-6.75	0.58-0.95	26.53-65.06
CO (g/km)	0.48-0.58	0.52-0.62	1.78-4.79	0.48-0.55	0.53-0.58	1.78-3.07
ICE Power (kW)	120.8-149.5	108.6–149.7	108.5-149.5	115.7-149.6	129.6–149.7	108.5-149.5
Motor Power (kW)	76.3-149.1	137.3–148.7	109.1 –149.8	82.3-148.6	115.8-149.9	109.2-149.8
ESS Capacity (Ah)	65.0-158.5	88.5–174.2	79.7–155.8	70.6.0-166.5	145.9–177.2	79.7-155.8
off_trq_frac	0.05-0.98	0.15-0.93	0.02 - 0.93	0.15-0.98	0.19-1.00	0.02-0.93
min_trq_frac	0.08-0.96	0.01-0.93	0.00–1.00	0.07-0.85	0.69-0.99	0.00–1.00
charge_trq	4.4-29.5	2-17.4	0.0-29.6	1.4-28.2	2.9-22.7	0.00-2.96
ele_spd_lo	1.06-2.60	1.40-2.66	1.00-2.79	1.16-2.79	1.31-2.74	1.00- 2.79
ele_spd_hi	3.0-5.41	2.92-4.89	3.11–5.50	2.99-5.09	3.30-5.38	3.11–5.50

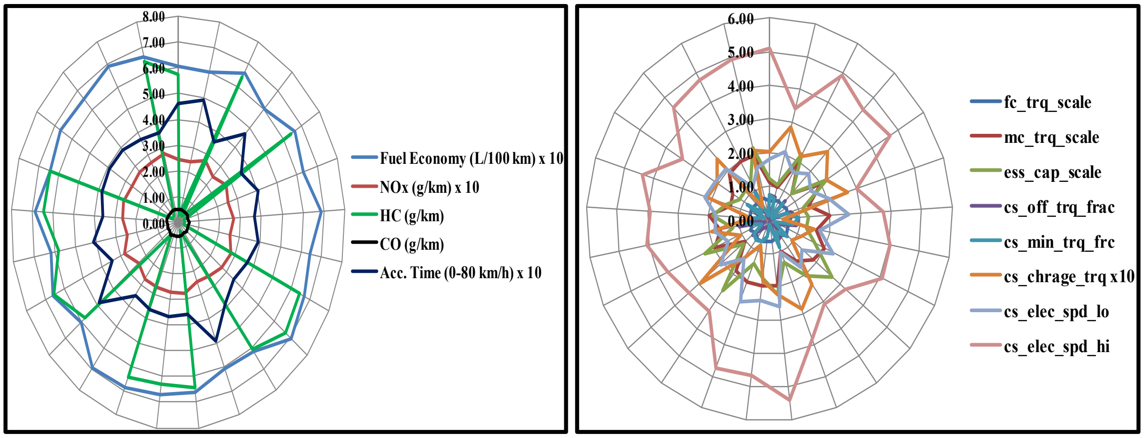


Fig. 4-15 Objectives and design variables: UDDS drive cycle-electric assist control

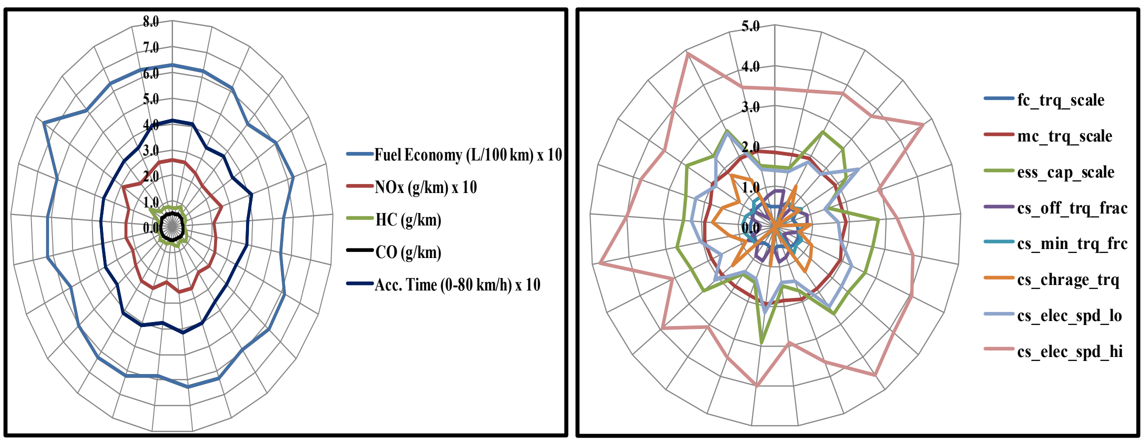


Fig. 4-16 Objectives and design variables: Montreal Pie-IX drive cycle-electric assist control

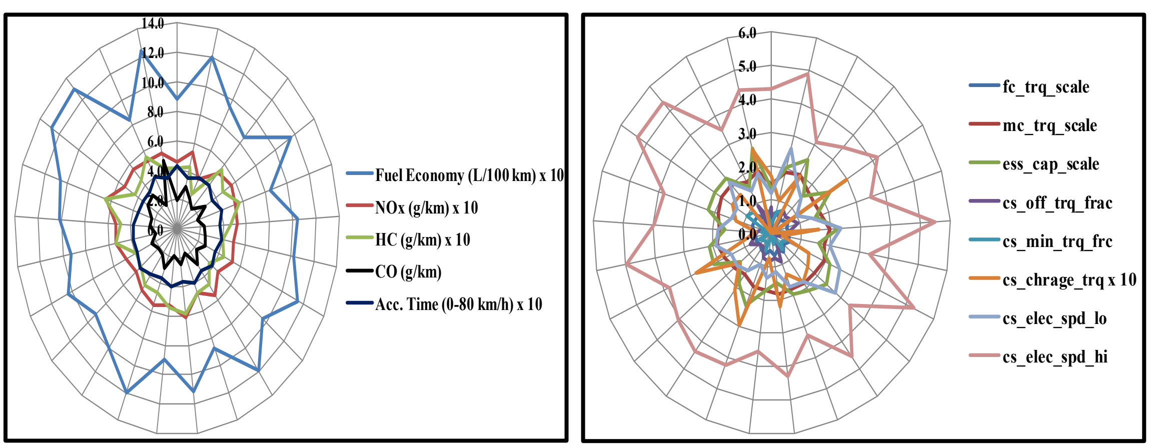


Fig. 4-17 Objectives and design variables: New York bus drive cycle-electric assist control

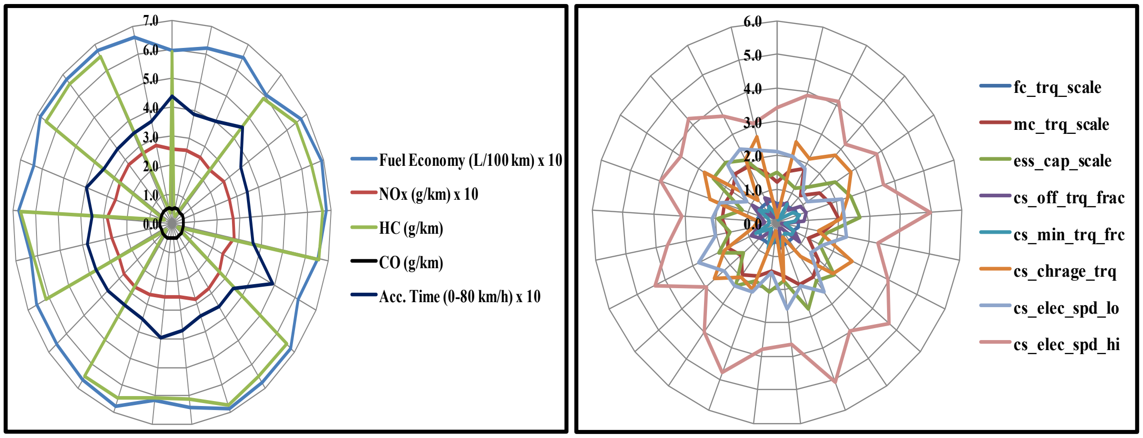


Fig. 4-18 Objectives and design variables: UDDS drive cycle-fuzzy logic control

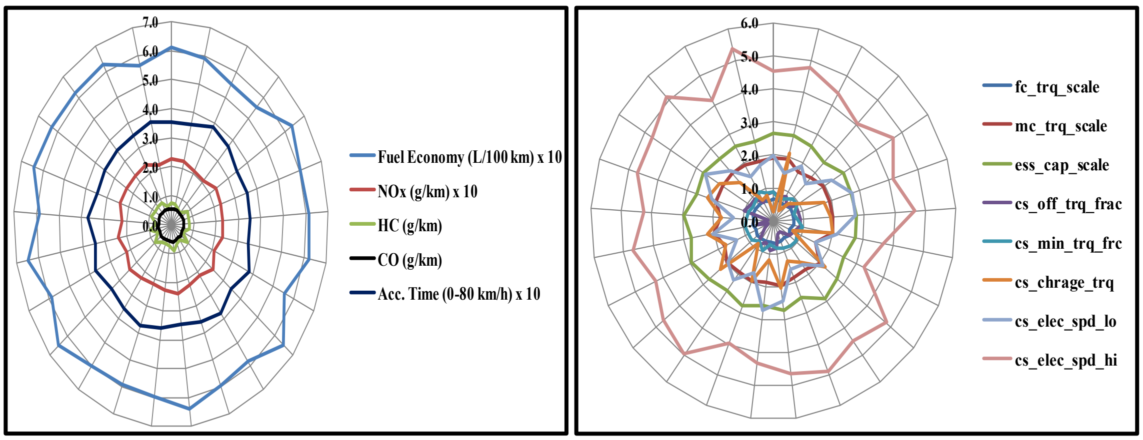


Fig. 4-19 Objectives and design variables: Montreal 139 Pie-IX drive cycle-fuzzy logic control

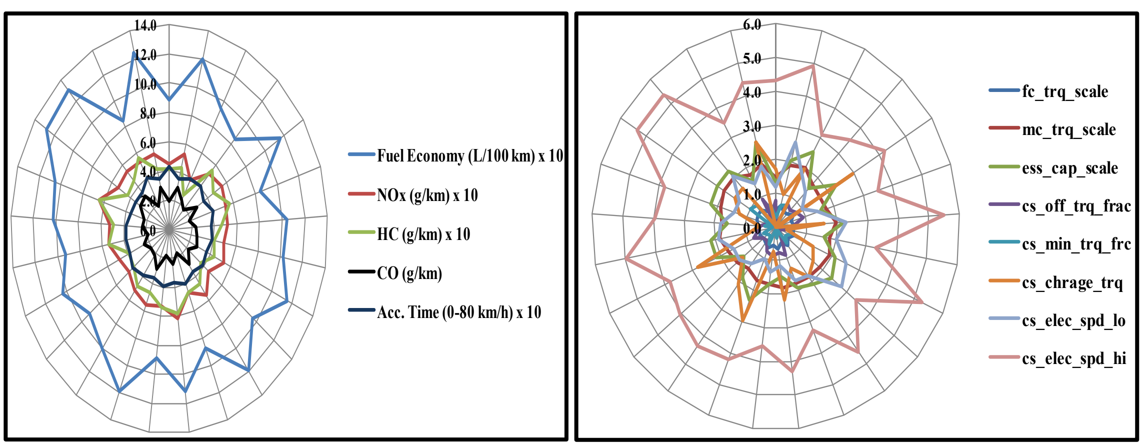


Fig. 4-20 Objectives and design variables: New York bus drive cycle-fuzzy logic control

A set of trade-off (Pareto-optimal) solutions is extremely helpful. If the fuel economy is the designer's top concern, then they can select a solution having highest fuel economy. Similarly, a solution having lowest value of emissions can be selected, if low emissions are priority for designers. The selection procedure is also affected by the variables, besides the objectives. If the size of an ICE or EM or ESS indicated by a particular solution, for instance, is not accepted by the designers for some reason, or if some control strategy parameters are not suitable for the vehicle, designers can substitute other solutions with similar values of objectives and/or design variables from a set of trade-off solutions. Thus, the decision making procedure becomes very flexible, with trade-off optimal (Pareto-optimal) solutions set.

Flexibility measure can be calculated in obtained trade-off solutions using equations 4-8 and 4-9, respectively. Fig. 4-21 to Fig. 4-26 graphically represents calculated flexibility measure in obtained solutions. The orange area of each bar indicates the flexibility of related the parameter. For all objectives, the total length of each bar corresponds to the obtained maximum value of the objective for all variables; the total length of each bar corresponds to the upper bound of the variable.

$$\text{Flexibility of objectives} = \frac{\text{max. (objective value)} - \text{min.(objective value)}}{\text{max.(objective value)}} \times 100\ \% \quad (4\text{-}8)$$

$$\text{Flexibility of variables} = \frac{\text{max. (variable value)} - \text{min.(variable value)}}{\text{variable upper bound} - \text{variable lower bound}} \times 100\ \% \quad (4\text{-}9)$$

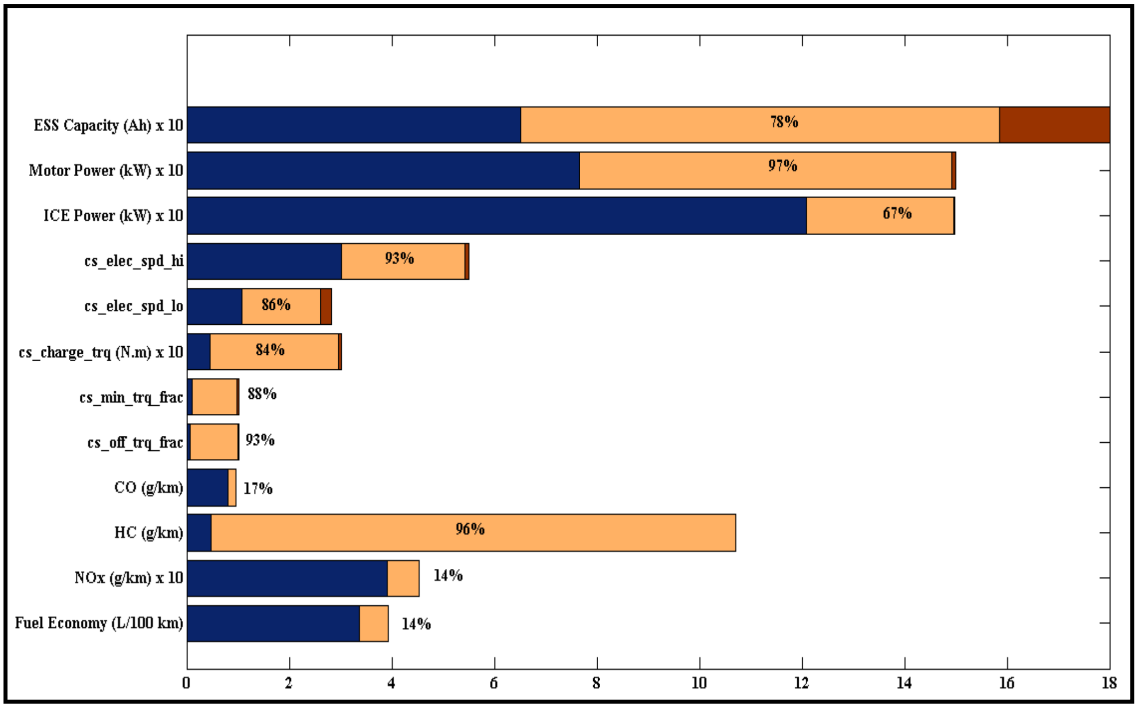


Fig. 4-21 Flexibility: UDDS drive cycle electric assist control

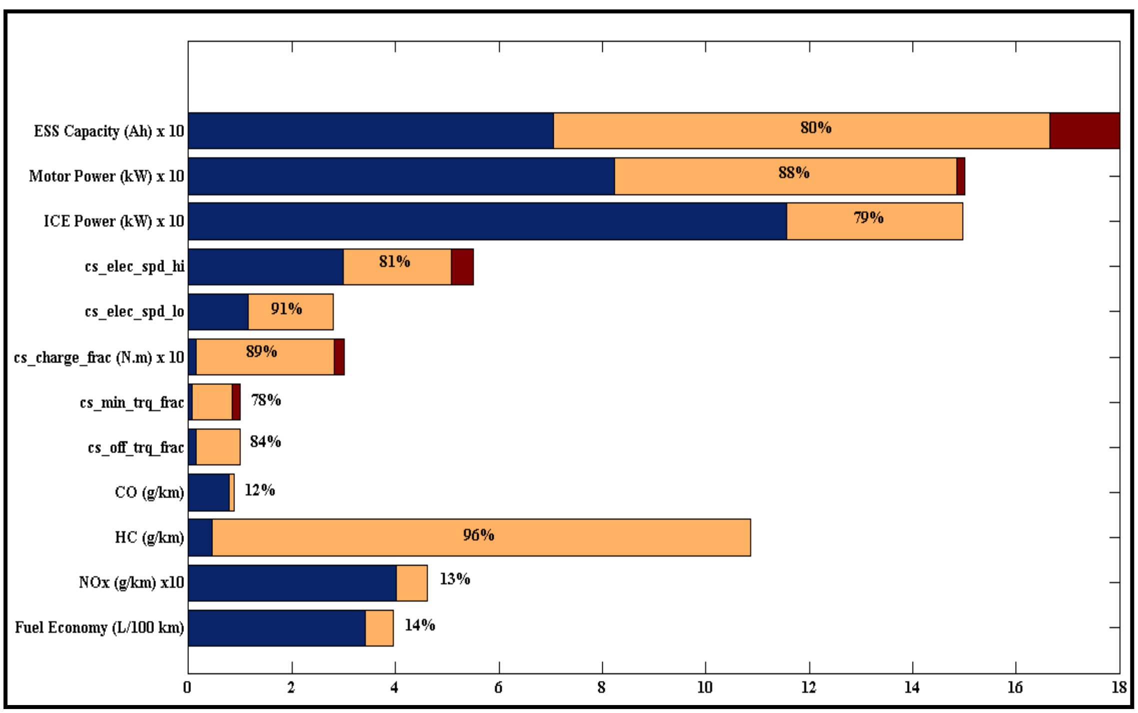


Fig. 4-22 Flexibility: UDDS drive cycle fuzzy logic control

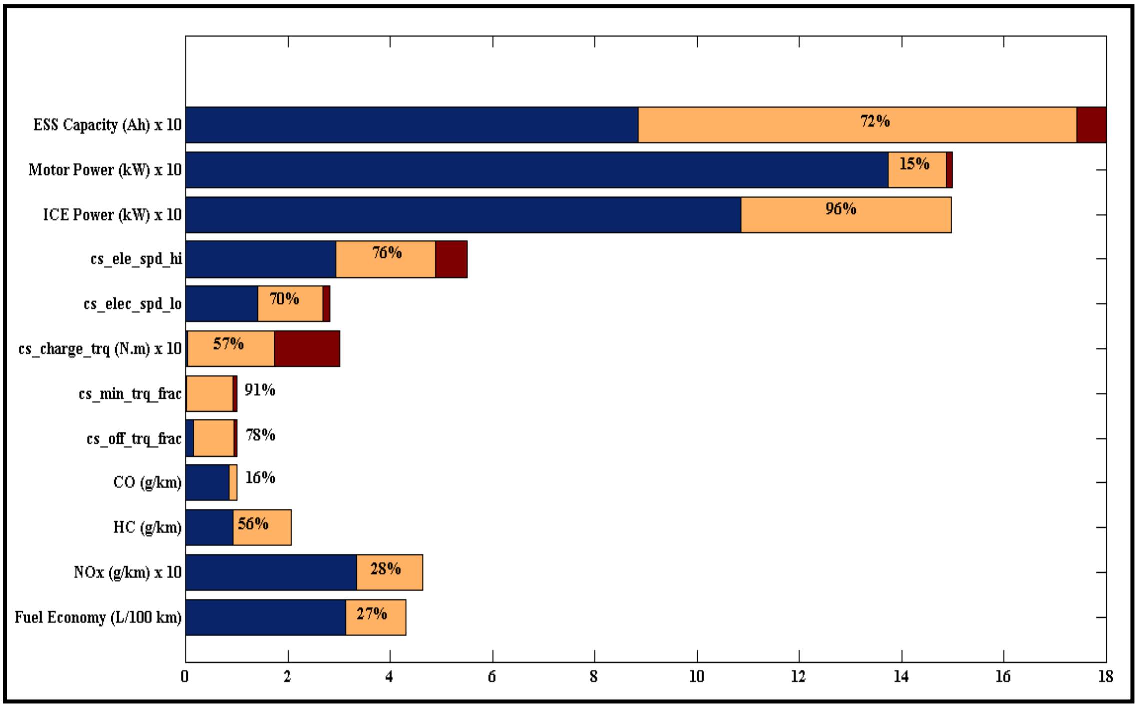


Fig 4-23 Flexibility: Montreal 139 Pie-IX drive cycle electric assist control

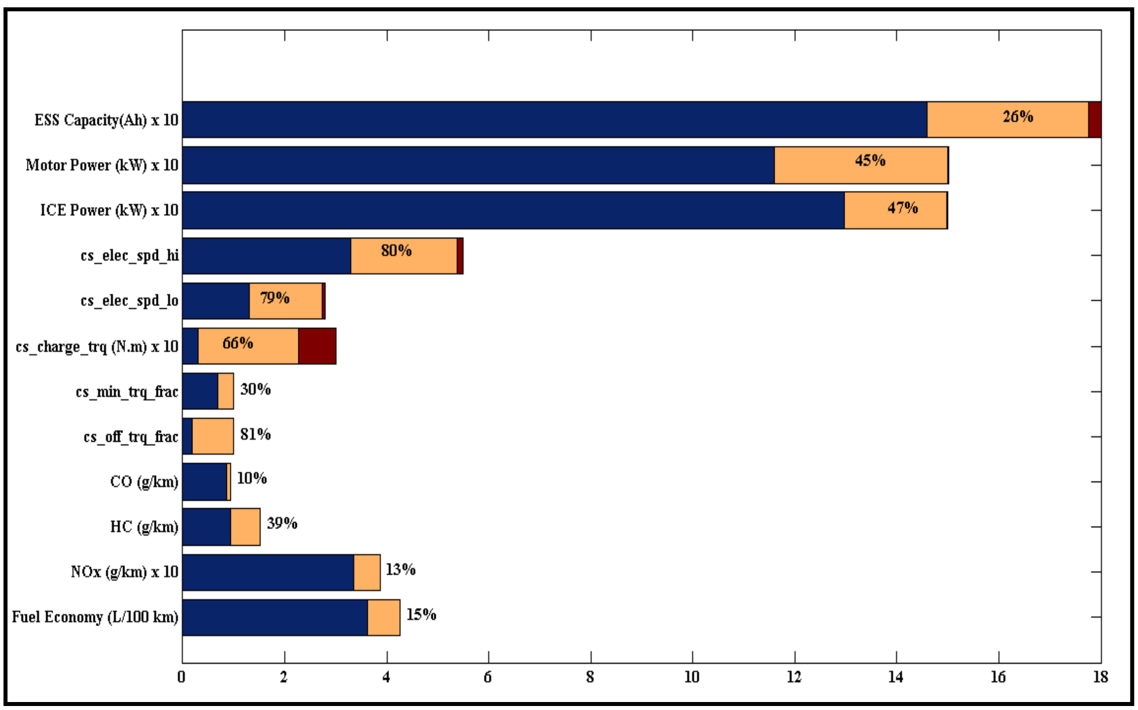


Fig. 4-24 Flexibility: Montreal 139 Pie-IX drive cycle fuzzy logic control

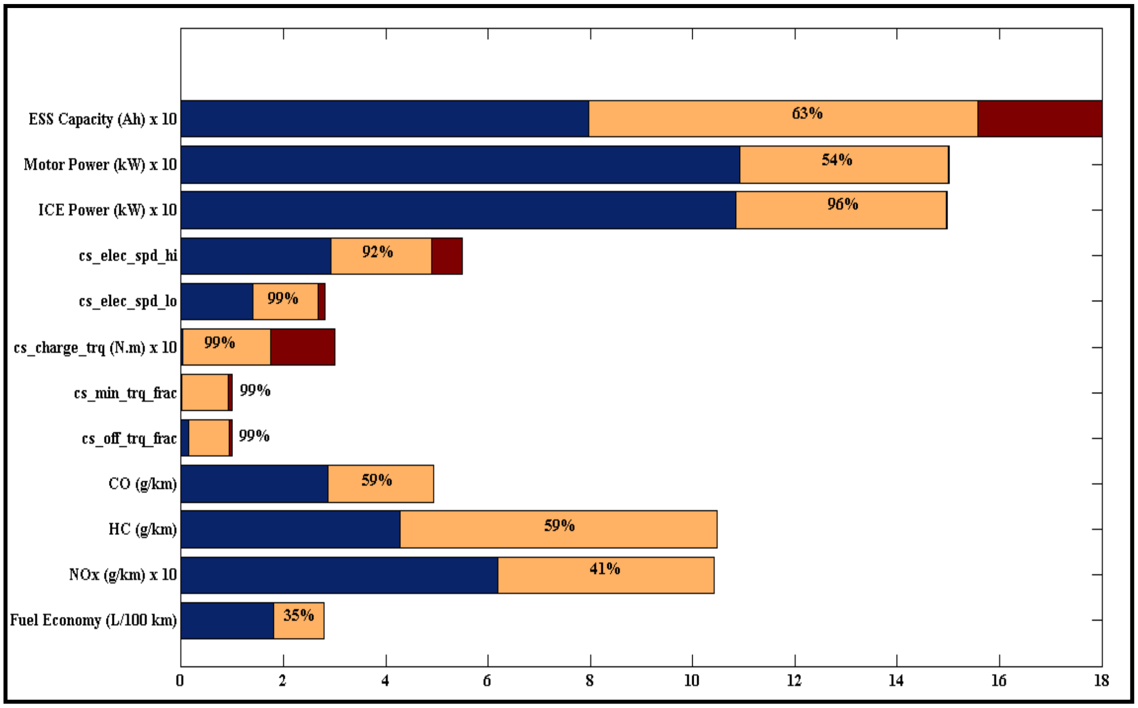


Fig. 4-25 Flexibility: New York bus drive cycle electric assist control

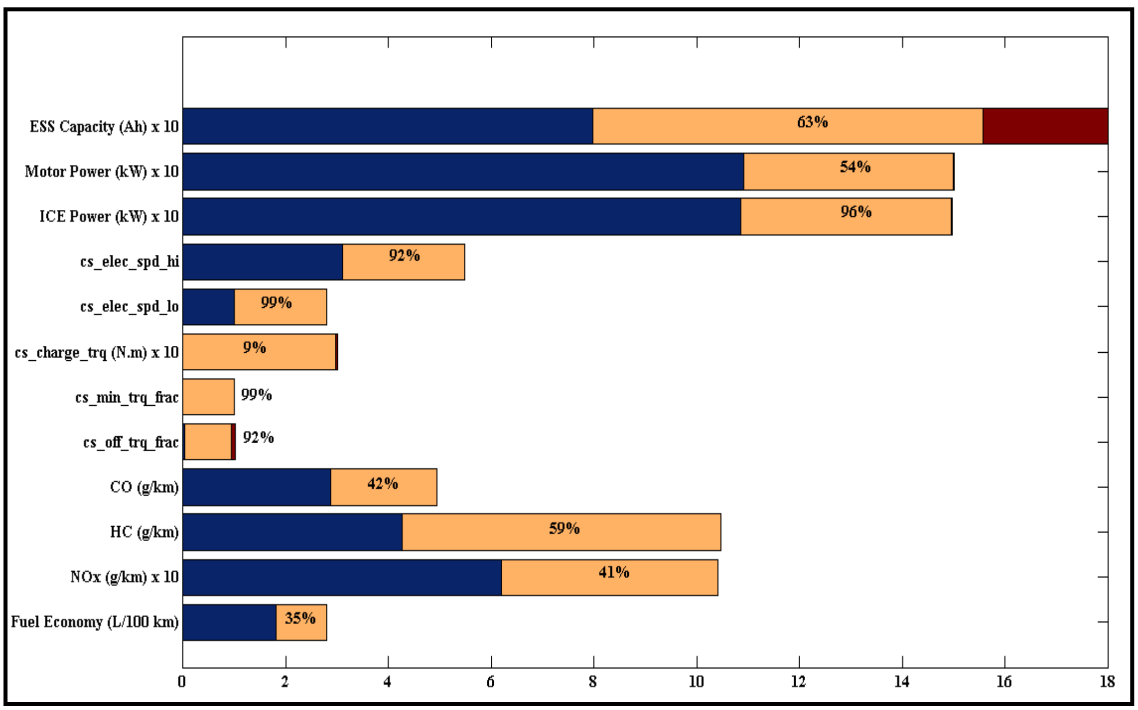


Fig. 4-26 Flexibility: New York bus drive cycle fuzzy logic control

4.7 COMPARISON AND ANALYSIS

Here, the traditional NOVA bus performance parameters are compared with the post-optimized trade-off solutions. For qualitative analysis, the traditional bus fuel economy, emissions and engine power are compared with a solution having minimum value among obtained trade-off solutions. The comparison is summarized in Table 4-15.

Table 4-15 Parameter improvement

	Electric Assist Control			**Fuzzy Logic Control**		
	UDDS Drive Cycle	**Montreal Pie- IX 139**	**NY Bus Drive Cycle**	**UDDS Drive Cycle**	**Montreal Pie- IX 139**	**NY Bus Drive Cycle**
Fuel Economy (L/100 km)	-13%	-30%	-65%	-14%	-31%	-65%
NO_X (g/km)	-55%	-75%	-91%	-54%	-75%	-91%
HC (g/km)	-89%	-88%	-30%	-89%	-87%	-30%
CO (g/km)	+23%	-27%	-35%	+23%	-26%	-35%
ICE Power (kW)	-44%	-50%	-50%	-46%	-39%	-50%

Table 4-15 shows an improvement in fuel economy and reduction in ICE power for all drive cycles, using both control strategies. Emissions are also reduced considerably. However, while optimizing the parallel HEV, emissions during the manufacturing process of the mechanical and electrical drivetrain components were not considered. Thus, from the global emission point of view, it is found that the obtained trade-off solutions of emissions are merely locally optimized.

Based on the obtained results, it can be inferred that among the two control strategies, the fuzzy efficiency control strategy leads to enhanced performance. By using fuzzy efficiency control, in the UDDS drive cycle diminutive improvement in fuel economy is observed. For the Montreal 139 Pie-IX drive cycle, number of solutions with noticeable improved value of fuel economy and emissions are obtained using fuzzy efficiency control strategy. However, not much improvement is observed using fuzzy efficiency control on New York Bus drive cycle. In the simulation of NOVA hybrid transit bus on UDDS and Montreal 139 Pie-IX drive cycle, using fuzzy efficiency control, increased value of energy capacity, engine off torque fraction and electric launch speed shows that the strategy uses more electric energy, which improves fuel economy. Moreover, it is also observed that the value of engine minimum torque fraction and charge torque values are increased, which causes the engine to operate in an efficient region and maintains SOC in the battery. Thus, overall drivetrain efficiency is also increased.

4.8 SUMMARY

In this study, the fuel economy and the emission optimization of a NOVA parallel hybrid electric transit bus is formulated as a constrained nonlinear optimization problem. The problem objectives, viz., fuel economy and emissions, are optimized simultaneously using NSGA-II, with design variables ICE size, motor size, ESS capacity, as well as control strategy parameters. Test results, demonstration, using interactive plots, projects a significant improvement in vehicle performance, compared to a conventional vehicle. In addition, the star-coordinate, flexibility, quantitative, and qualitative evaluation provides a firm selection platform for objectives, drivetrain components, and control strategy parameters for HEV designers.

It has been found that MOEA projects a tremendous potential for HEV design problems, involving numerous local minima, discontinuity in objective function, and nonlinear constraints. Moreover, MOEAs do not require any user dependent artificial fix-up or information about derivative of objectives. It can find multiple trade-off solutions in a single simulation run.

CHAPTER 5

PLUG-IN HEV (PHEV) OPTION FOR NOVA TRANSIT BUS

5.1 INTRODUCTION

Plug-in hybrid electric vehicles (PHEVs) are similar to conventional hybrid electric vehicles, except that they are equipped with a larger battery and plug-in charger that allows electricity from the grid to replace a portion of the petroleum-fueled drive energy [46]. PHEVs may derive a substantial fraction of their miles from grid-derived electricity, but without the range and charging time restrictions of pure battery electric vehicles. In addition to reducing petroleum consumption, PHEVs have the potential to also reduce total energy expenses for the owner and the electric power industry. Existing commercial hybrid vehicles have proven to be successful components of the transportation system worldwide.

PHEVs use grid electricity from diverse domestic energy sources, such as renewable, coal, and nuclear, thus reducing the nation's demand for imported oil. PHEVs demonstrate better performances where total distance traveled comprise of relatively shorter trips [47]. By recharging the energy storage system (ESS) between these short trips, a large portion of the motive energy can come from the electrical grid as opposed to gasoline or other fossil fuels. Similar concept can be used for STM NOVA transit bus. Energy storage of transit bus can be charged before beginning or after finishing of each trip or it can be charged at central bus depot. In this way, transit bus can run all-electrically during most of the time of its trip. In the present urban transit environment, charging infrastructure, integration of renewable energy sources as a source of charging power are necessary to be investigated in the near future.

In this chapter, possible future plug-in version of NOVA parallel hybrid transit is discussed along with modified structure of a plug-in hybrid drivetrain. PHEV Control strategy with their merits and demerits are discussed.

5.2 NOVA PHEV TRANSIT BUS DRIVETRAIN

The drivetrain of the PHEV NOVA transit bus is illustrated in Fig. 5-1. For modeling, a NOVA low floor transit bus database, available in ADVISOR, has been used.

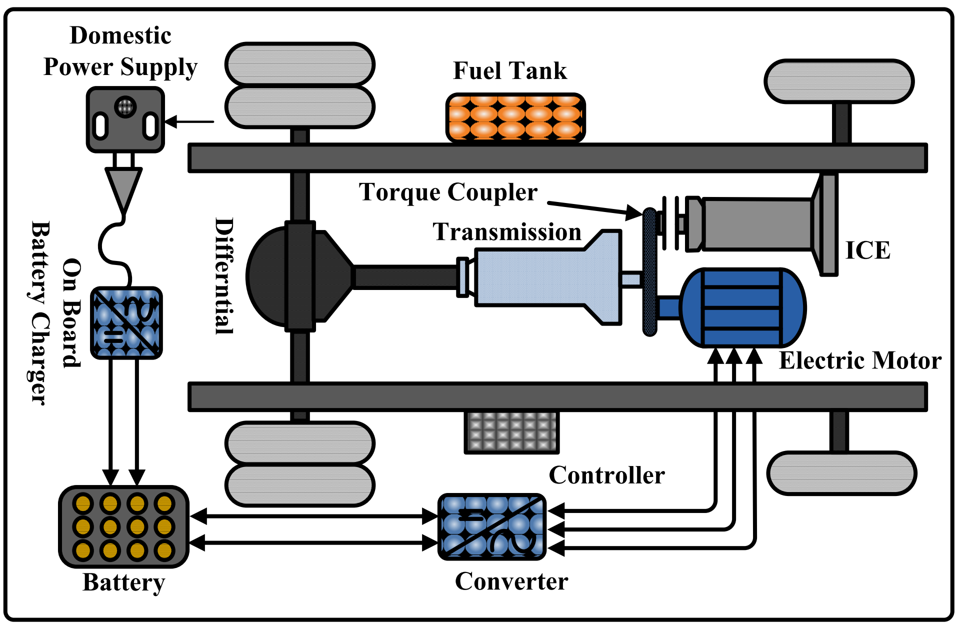


Fig. 5-1 NOVA plug-in hybrid (PHEV) transit bus drivetrain

In order to rely mostly on ESS module energy for the several miles of the drive cycle, PHEVs are equipped with higher energy capacity ESS. As long as ESS is not completely depleted, PHEVs can run all electrically. Afterwards, it operates like a regular HEV. Such a vehicle can be plugged in and charged off the grid. The ESS module energy capacity of PHEVs is larger than existing parallel HEVs, though it is not as large as the

ESS modules in electric vehicles [48]. In some cases, ultra-capacitors (UCs) and/or fly wheels can be hybridized with a battery pack, to further enhance the vehicle dynamic performance. Moreover, UCs can charge rapidly from the grid, by charging UCs at any stop of drive cycle and stored UCs energy can be transferred to battery pack during normal driving. This method reduces the overall charging time of battery and increases all electric range of transit bus. Few terminology associated with plug-in hybrid vehicle are discussed below.

(1) Charge-sustaining (CS) mode – A mode of operation in which the state-of-charge of the energy storage system over a drive cycle may increase and decrease however, at the end of every drive cycle it will come back to a state with equivalent energy as at the start of the period.

(2) Charge-depleting (CD) mode – A mode of operation in which the state-of-charge of the energy storage system over a drive cycle will have a net decrease in stored energy.

(3) All-electric range (AER) – The total distance driven electrically from the beginning of a drive cycle to the point at which the engine first turns on.

(4) Electrified miles –Summation of all miles driven electrically (ICE off) including those after the engine first turns on.

(5) PHEV xx – A plug-in hybrid vehicle with adequate energy to drive xx miles electrically on a defined drive cycle generally assumed to be city driving. The vehicle may or may not actually drive the initial xx miles electrically. It total depends on the behaviour of driving and the control strategy.

5.3 PHEV CONTROL STRATEGY

In the previous chapter we stated that the vehicle control strategy has considerable effects on the performance of the PHEV. PHEVs are equipped with one or more energy sources for propulsion. Moreover, PHEVs fuel economy is highly affected by total vehicle mile travelled.

5.3.1 ALL-ELECTRIC RANGE (AER) FOCUSED STRATEGY

In the all-electric range (AER) focused strategy, PHEV operates all-electrically during almost the full range of CD operation and the motor supplies the overall vehicle power demand, and the engine remains off. Fig. 5-2 illustrates the AER-focused strategy operation. Before driving, the vehicle ESS is fully charged. The SOC drops during the CD operating distance as the vehicle drives electrically without any assistance from the engine. Thus, a quiet and smooth all electric operation with zero emissions can be realized. Once SOC reaches at CS SOC level, the SOC remains roughly steady while the engine and motor work together during CS operating mode.

In order to realize all-electric CD operation in AER-focused strategy, motor and ESS power capability should at least match the maximum power requirement of the drive cycle. However, to meet the driver's demand for a given drive cycle, the peak power rating of the ESS needs to be high, which increases the cost of the vehicle. The control strategy is fixed and the ICE is always off until the CS mode begins. This may result in ESS being damaged during aggressive drive cycles when the driver demand is greater than the ESS peak power capability.

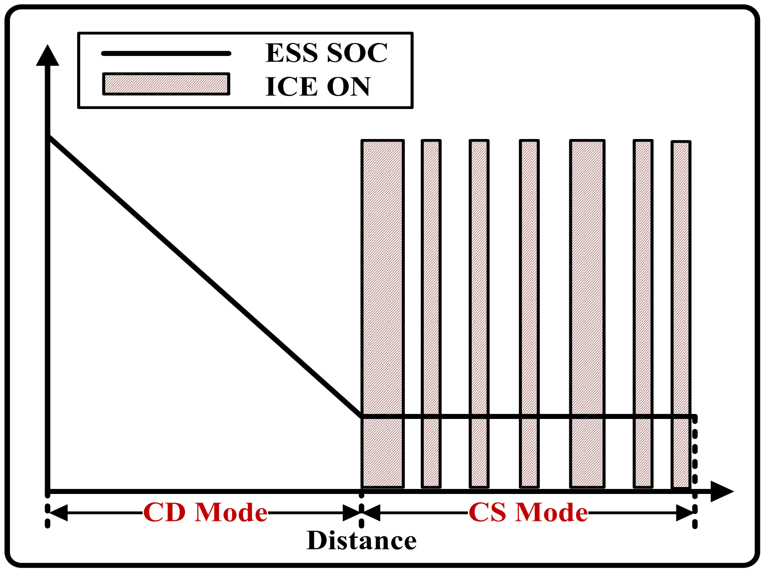


Fig. 5-2 PHEV all electric range (AER) focused strategy: ICE usage and SOC profile

In PHEV, total driving distance between vehicle recharge influences the amount of petroleum displacement provided. For example, a PHEV is designed for the driving distance equal or less than the AER, the AER-focused strategy provides maximum petroleum displacement, and the ICE remains off and uses no fuel. For larger driving distances, the fuel consumed during CS operation is divided into the full CD plus CS distance to determine the average petroleum fuel economy for that particular driving.

5.3.2 Engine-Dominant Blended Strategy

In the engine dominant blended strategy, the ICE is the primary source of power and the ESS is used to assist the ICE. Stored energy expands the ICE operation in order to improve system efficiency. Fig. 5-3 demonstrates the engine dominated blended strategy operation. The Vehicle started with a fully charged ESS may operate all-electrically during initial CD operation. However, the ICE turns on during the CD mode as soon as the vehicle power demand exceeds the power capability of the battery and motor. After the ICE turns on, the ESS supplements the ICE power to maximize ICE or drivetrain efficiency. Motor supplies power only when power demand is greater than the maximum capacity of the ICE, negative power demand (regenerative braking) and at the low speed operation where the ICE would be inefficient. This strategy starts using the ICE energy from beginning of cycle and uses the ICE more often as compared to the AER focused strategy. The CD distance increases because of frequent use of the ICE.

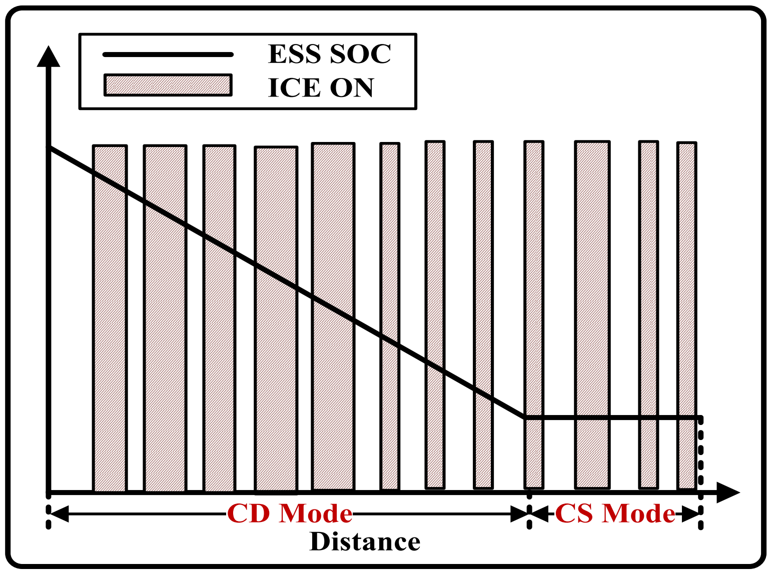


Fig. 5-3 PHEV engine-dominant blended strategy: ICE usage and SOC profile

An engine-dominant blended PHEV uses much smaller and inexpensive electrical components. We can see that the engine-dominant strategy can be operated in a very similar way of present-day HEVs electrical assist control strategy, simply by making more use of electrical assist during CD operation. Hence, there is no need to change the power capacity of the electric component than that of existing HEV components. In order to drive considerable distance in CD mode, the energy capacity of the ESS needs to increase than that of present HEVs.

5.3.3 ELECTRIC-DOMINANT BLENDED STRATEGY

An electric, ESS/motor dominant blended uses mainly ESS energy to supply necessary power when ESS exhibits a high state of charge and driving demand is not greater than the power capability of ESS and motor. As the SOC of the ESS begins to decrease, the strategy uses more ICE energy in order to satisfy power demand, maintain ESS SOC, avoid ESS damage and reduced cycle life. Fig. 5-4 illustrates energy sharing between ESS and ICE on drive cycle. Vehicle operates all electrically only until driving requirement does not exceed ESS and motor power. As ESS SOC decreases, ICE usage increases, which maintains the ESS SOC.

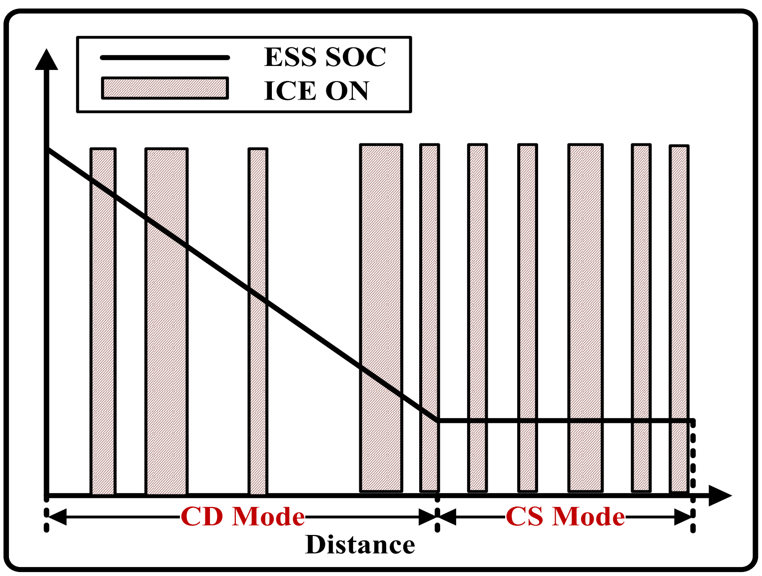


Fig. 5-4 PHEV electric-dominant blended strategy: ICE usage and SOC profile

The parameters of electric-dominant blended control strategy used in ADVISOR are listed in Table 5-1, which are exactly similar to that of the parallel electric assist control strategy. Electric launch speed logic of PHEV blended control strategy is presented graphically in Fig. 5-5. State of the ICE can be determined using current values of ESS SOC and vehicle speed. In Fig.5-5, above solid line the ICE is on and below solid line the vehicle attempts to run all electrically. Following rules decide ICE on-off state in charge-depleting blended mode.

ICE can be turned off:

1) When vehicle speed is less than electric launch speed.

2) When vehicle is decelerating, during which torque demand is negative.

ICE must be on:

1) When ESS/motor capacity is inadequate to supply the requested power.

Table 5-1 PHEV blended control strategy parameters

Parameters	Description
cs_lo_soc	Lowest desired battery SOC
cs_hi_soc	Highest desired battery SOC
cs_electric_launch_speed_lo	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at low battery SOC
cs_electric_launch_speed_hi	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at high battery SOC
cs_charge_trq	Additional torque required from engine to charge or discharge the battery based on battery SOC
cs_off_trq_frac	Fraction of ICE max. torque at each speed at which ICE should turn off when SOC > (cs_lo_soc)
cs_min_trq_frac	Fraction of ICE max. torque at each speed above which ICE must operate if SOC < (cs_lo_soc)

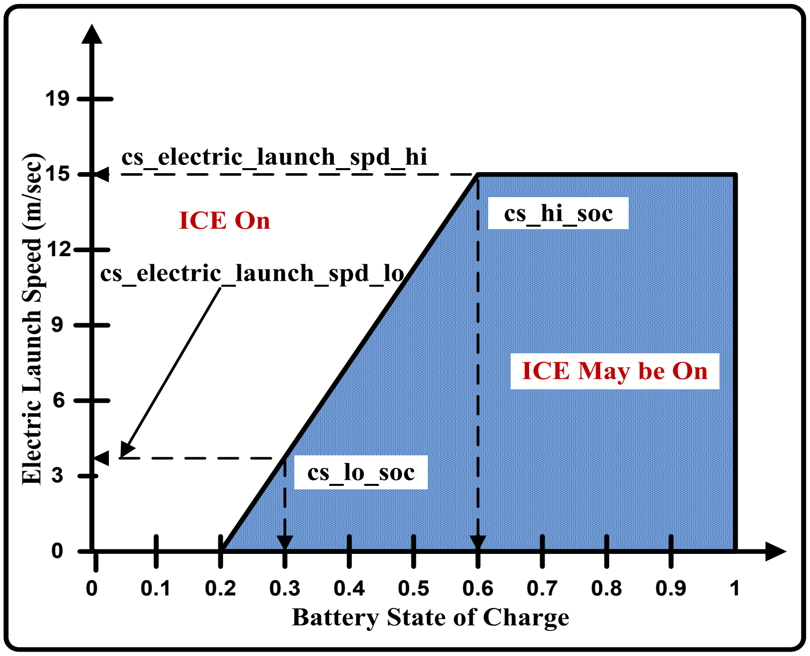


Fig. 5-5 PHEV electric launch speed logic

The logic of ICE torque modification is illustrated in Fig. 5-6. When the ICE is on, torque requested from ICE may be modified based on the current ESS SOC status to deliver more or less power from ESS, which executes ESS charging or discharging, respectively. The strategy requests an additional charge torque from ICE (cs_charge_trq) when current ESS SOC is at minimum level (cs_lo_soc). In Fig.5-4 torque is modified from point (2) to point (4). Negative charge torque (– cs_charge_trq) is requested when ESS SOC is at high level (cs_hi_soc), ICE point of operation is modified from point (2) to point (3). ICE may work at point (1), a minimum engine torque (cs_min_trq_frac), if the ESS SOC drops below minimum SOC level (cs_lo_soc).

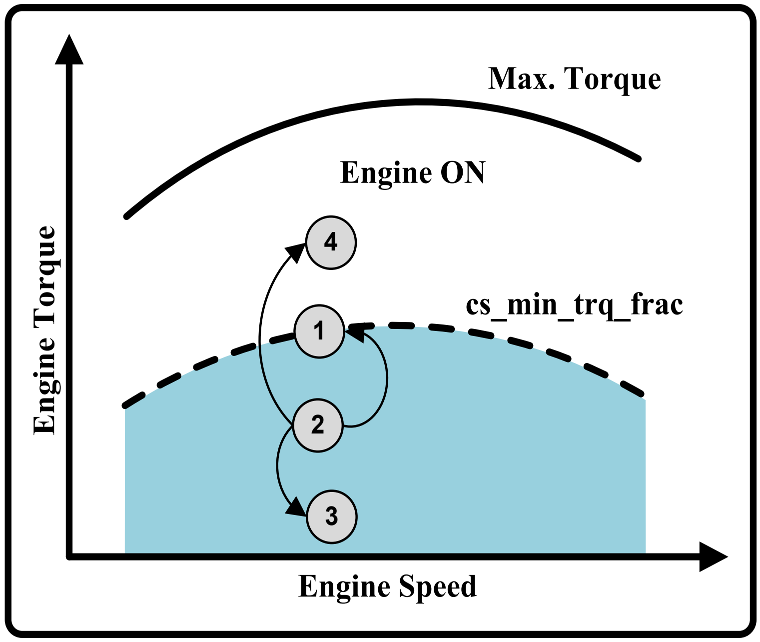


Fig. 5-6 ICE torque modification

Due to intermittent engine operation during the CD mode, PHEV with electric-dominant strategy cannot get zero emission vehicle credit. However, petroleum displacement rate during the CD mode will still be the same as that for AER-focused PHEVs. When driving greater CD distance, the electric-dominant blended strategy will consume slightly more fuel as compared with engine-dominant blended strategy, due to less focus on maximizing engine efficiency throughout all driving modes. However, for driving much less than CD distance, the electric-dominant blended strategy will consume considerably less fuel due to greater utilization of ESS recharge energy.

5.4 SUMMARY

PHEV design and potential advantages are highly affected by the choice of CD operating strategy. The AER-focused strategy requires larger and costly electric equipments. However, AER-focused strategy gives all-electric cycle operational benefits, as well as it can receive more credits for zero emission vehicle (ZEV) regulation. The engine-dominant and electric-dominant blended strategies do not provide much all-electric operation benefits, but PHEV implemented with these strategies required much smaller and less expensive electric components. The AER-focused strategy is mainly sensitive to cycle aggressiveness because this strategy is not able to satisfy significant power demands during the CD mode all-electrically.

The engine-dominant blended strategy is particularly sensitive to driving distance, as the vehicle must exceed the CD distance in order to benefit from the efficiency maximization approach. For shorter driving distances, the engine-dominant blended strategy will have a significant fuel use penalty as compared to the other strategies due to under utilization of the electrical recharge energy.

In electric-dominant blended strategy, the PHEVs are designed to accommodate large intermittent power demands, due to which the cycle aggressiveness does not have a huge impact. However, the resulting intermittent low-power engine operation will present unique emissions control system challenges for this type of PHEVs.

CHAPTER 6

HYBRID ELECTRIC VEHICLE CONTROL STRATEGY DESIGN USING STATEFLOW

6.1 INTRODUCTION

In recent years, graphical modeling and simulation techniques have become increasingly popular for the development of automotive control systems. However, the power and high degree of freedom offered by these tools can also lead to problems, if not used properly, especially in large projects. Guidelines can help establish a consistent modeling style throughout a project, and thus, improve readability, understanding ability, and maintainability of the resulting product. The Stateflow chart is an interactive graphical design tool that works with Matlab/Simulink, to model and simulate event-driven systems, also called reactive systems. Stateflow provides clear and brief descriptions of complex system behaviour, using finite state machine theory, flow diagram notations, and state-transition diagrams [49].

In this chapter, graphical modeling technique using Stateflow will be described. Moreover, as an initial step to future research in the field of HEV control strategy development, the design of a series HEV control strategy, using Stateflow, is demonstrated.

6.2 STATEFLOW AND CONTROL STRATEGY DESIGN

Stateflow is a Matlab/Simulink interactive graphical design tool for constructing hierarchical state machines to represent discrete-state and discrete-event behaviors in dynamic systems. Stateflow uses a variant of the finite state machine notation, found by Harel [50]. Stateflow diagrams can be connected to continuous-state blocks in Simulink, to model hybrid dynamic systems, which are systems consisting both continuous state variables as well as discrete state variables. These models can be used to investigate the model behavior under various operating conditions by simulation. The graphical design technique of Stateflow, in combination with Simulink, allows:

1. Design and build up of deterministic and supervisory control systems;
2. Visual modeling and simulation of complex even-driven (reactive) systems, based on finite state machine theory;
3. Alter design, evaluate the results, and validate system performance at any stage of the design;
4. Generate integer, floating-point, or fixed-point code directly from the design.

In a Stateflow diagram, states and transitions form the basic building blocks of the system. Flow diagram notation creates decision-making logic, such as FOR loops and IF-THEN-ELSE constructs, without the use of states. In some cases, using flow diagram notation provides a closer representation of the required system logic that avoids the use of unnecessary states.

In the ADVISOR series HEV architecture, the state machine part of the vehicle system controller decides the operating mode of the vehicle. To categorize the states for the state machine, for all subsystems, the sets of all possible operating modes are listed.

As an example, for the engine turn on and turn off logic, the possible operating modes are engine on and engine off. To construct the suitable switching strategy, transition conditions between on and off operating modes must be established. Many control strategy parameters make decisions to select operation mode, such as fuel converter off period (fc_off_time), the value of ESS SOC, required bus power (bus_pwr_req), ESS maximum power (ess_max_pwr), FC power commanded (fc_pwr_com), and the minimum power of the fuel converter (cs_min_pwr). Turn on and turn off rules for fuel converter operations are listed below.

FC turn off rules:

1) Required bus power is less than ESS max. power AND required fuel converter power (fc_pwr_com) is less than minimum fuel converter power (cs_min_owr) and ESS SOC greater than 90% of (cs_hi_soc)

OR

2) Required bus power is negative (regeneration) and fuel converter minimum power is greater than the difference of required bus power and ESS charge power.

FC turn on rules:

1) Required bus power is greater than ESS maximum power.

OR

2) Value of ESS SOC drops below minimum SOC level (cs_lo_soc) AND required bus power (bus_pwr_req) is positive OR difference of required bus power and ESS charge power is higher than FC minimum power.
3) FC off time is higher than set minimum off time AND required bus power is higher than minimum FC power AND ESS SOC value is less than the average of the highest and lowest desired ESS SOC AND required bus power is

positive OR difference of required bus power and ESS charge power is higher than FC minimum power.

ADVISOR series HEV fuel converter turn on/off logic, modeled in Simulink, is shown in Fig. 6-1. Fuel converter turn on/off logic design using Stateflow is presented in Fig. 6-2.

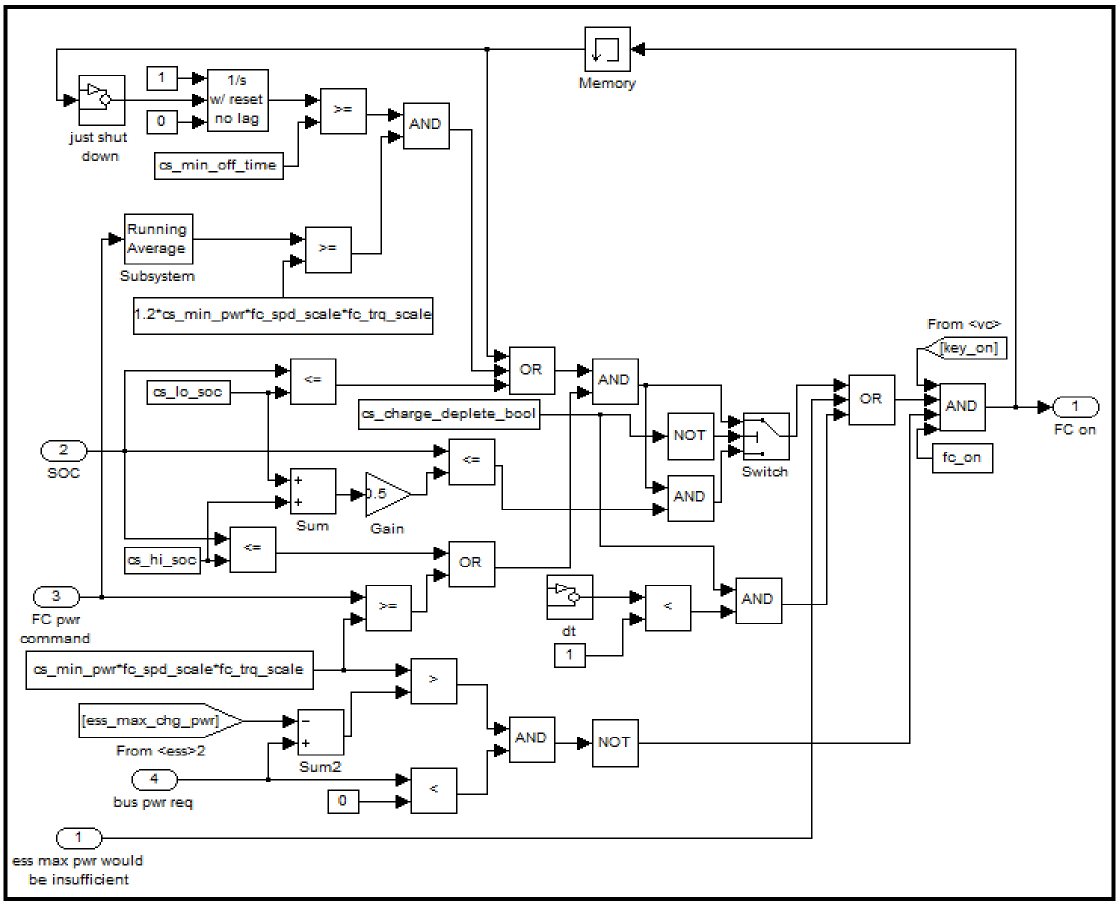


Fig. 6-1 ADVISOR series HEV fuel converter turn on/off logic using Simulink.

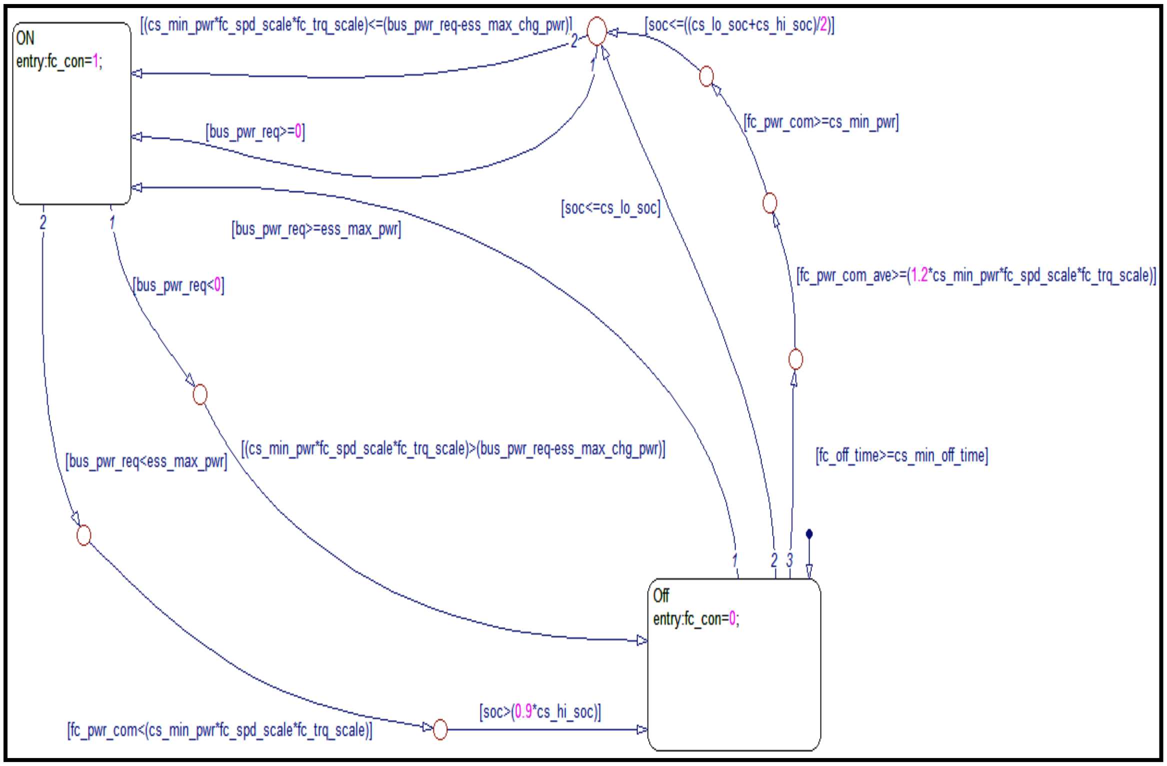


Fig. 6-2 ADVISOR series HEV fuel converter turn on/off logic using Stateflow

It is clear from Fig. 6-2 that modeling using Stateflow simplifies the overall design procedure. Moreover, visual interaction with FC on/off states during simulation run provides the option of visual inspection, which is not possible with Simulink.

During the simulation phase, designers can modify the design at any stage, which increases the possibility of obtaining optimal results, with minimum to zero error. The overall block diagram, upon implementing FC on/off logic, using Stateflow, is shown in Fig. 6-3.

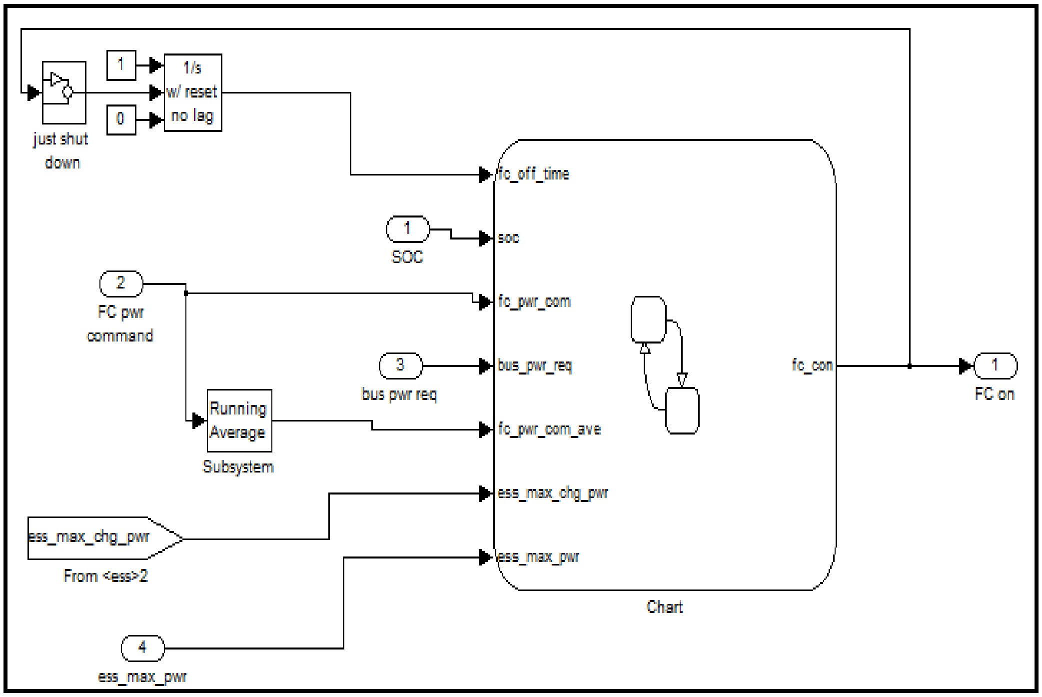


Fig. 6-3 Series HEV fuel converter turn on/off block

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

7.1 SUMMARY

Hybrid electric vehicle (HEV) parameter optimization is a multidisciplinary research topic. In the design of an HEV, the preliminary goal of the designer is to minimize fuel consumption and emission, along with best possible sizing of internal combustion engine (ICE), electric motor (EM), and energy storage system (ESS) with tuned CS parameters. Moreover, vehicle performance constrains also have to be satisfied. Classic weighted sum method, ε-constraint method, gradient-based, and derivative-free methods, for HEV parameter optimization, have been discussed. All of methods repeat simulations multiple times, with different weights and constraint values, to obtain multiple trade-off solutions.

In addition, all methods require strong assumptions for the objective function, so that appropriate weights, associated with objectives, can be specified. Moreover, the classic methods obtain only single solution for each objective, without any other information about trade-off among objectives. Weighted sum and ε-constraint strategy may result in a suboptimal solution, if the objectives trade-off results in non-continuous and/or non-convex behaviour in function space. These methods work on pre-defined rules, so they can only be efficient in solving special class of problems, and cannot be applied to a wide variety of problems.

However, population based MOEAs project a tremendous potential for HEV design problems, which involve numerous local minima, discontinuity in objective function, and nonlinear constraints. Moreover, MOEAs do not require any user supplied artificial fix-up or information about derivative of objectives, and can find multiple trade-off solutions in single simulation run.

In this research work, various hybrid electric vehicle energy management control strategies were classified, discussed, and contrasted in detail. The control strategies discussed varied from traditional on-off type thermostat control to advanced model predictive and adaptive control. In general, HEV control strategies are classified as rule-based and optimization-based. The classified control strategies were discussed, in general, and their sub-categories were introduced briefly, whereby their merits and demerits were highlighted.

Although global optimization-based strategies cannot be used in real-time applications, they provide a solid platform for design and comparison. From an online implementation point of view, optimal real-time and fuzzy rule-based methods are deemed highly suitable. Because of their adaptive and robust characteristics, fuzzy rule-based control strategies are superior, compared to deterministic rule-based methods.

Computational complexity is a major issue in analytical optimal control methods, since they are more memory intensive than fuzzy rule-based methods. Since analytical optimal methods are based on drivetrain models, any uncertainties in modeling would affect the controller. On the other hand, fuzzy rule-based methods are robust and insensitive to modelling uncertainties.

Information from the navigation system can be used for predictive and future control. However, this not only increases the number of inputs, but also makes for a much more complicated rule-based system. Nevertheless, the analytical optimal controller can obtain a semi-global solution without any complexity.

In this study, the fuel economy and emission optimization of a NOVA parallel HEV transit bus is formulated as a constrained nonlinear optimization problem. Problem objectives, viz., fuel economy and emissions, are optimized simultaneously using NSGA-II, with design variables as ICE size, motor size, and ESS capacity, as well as control strategy parameters. Test result demonstration, using interactive plots, projects a significant improvement in vehicle performance, compared to the conventional vehicle. In addition, the star-coordinate, flexibility, quantitative, and qualitative evaluation provides a firm selection platform for objectives, drivetrain components, and control strategy parameters for designers.

7.2 POTENTIAL FUTURE WORK

Presently, existing control strategies provide a fairly strong comparative view to the EV/HEV designer. However, there exist a few important points that can be considered for future development work. Energy storage devices are vital elements of EV/HEV drivetrains. Payback period, maintenance cost, and replacement cost of energy storage devices are strongly dependent on life and durability. Hence, it is advisable to design a control strategy keeping in mind extension of durability of the energy storage system. In future all-electric and plug-in hybrid electric vehicle architectures, additional energy storage components, such as ultra-capacitors and flywheels, will most definitely be incorporated, which will require innovative and efficient power management strategies.

In the present optimization work, 25 populations, 100 generations, and diversity in objective (phenotype) space was used. In order to ensure the effectiveness of NSGA-II, vehicle performance should be investigated with a higher number of population and generations, with diversity in objective (phenotype) as well as design variable (genotype) space.

Optimization was performed over different single drive cycles. Hence, to analyse the sensitivity of the obtained solutions, the optimization must be tested over different multiple drive cycles. Moreover, the vehicle was simulated with ambient temperature of drivetrain components and under normal weather conditions. Alternatively, the vehicle optimization and simulation could be performed with varying temperature and weather conditions.

The software ADVISOR was used in this analysis. The same transit bus optimization, using another vehicle modeling package, for instance, Powertrain System Analysis Toolkit (PSAT), may provide different results, due to different modeling approach and data sets. Moreover, the combination of Stateflow graphical modeling technique and NSGA-II evolutionary algorithm can lead to more efficient global optimal solutions.

The NSGA-II optimization algorithm can work on parallel machines. In order to reduce computational time, each of the independent function evolutions can be performed on separate processors or machines.

References

[1] Hybrid Transit Bus Certification Workgroup, "Engine certification recommendations report," *Northeast Advanced Vehicle Consortium* (NAVC0599-AVP009903), Sept. 2000.

[2] C. C. Chan, "The state of the art of electric, hybrid, and fuel cell vehicles," *Proceedings of the IEEE*, vol. 95, no. 4, pp. 704-718, April 2007.

[3] M. Ehsani, Y. Gao, S. Gay, and A. Emadi, *Modern Electric, Hybrid Electric, and Fuel Cell Vehicles*: *Fundamentals, Theory and Design*, FL: CRC Press, 2004.

[4] A. Emadi, K. Rajashekara, S. S. Williamson, and S. M. Lukic, "Topological overview of hybrid electric and fuel cell vehicular power system architectures and configurations," *IEEE Trans. on Vehicular Technology*, vol. 54, no. 3, pp. 763-770, May 2005.

[5] G. Maggetto and J. Van Mierlo, "Electric and hybrid electric vehicle: a survey," *IEE Seminar on Electric, Hybrid Electric, and Fuel Cell Vehicles*, Durham, UK, April 2005, pp. 1-11.

[6] Z. Rahman, K. L. Butler, and M. Ehsani, "A comparison study between two parallel hybrid control concepts," in *Proc. of SAE World Congress*, Detroit, MI, March 2000, Paper No. 2000-01-0994.

[7] A. Kimura, T. Abe, and S. Sasaki, "Drive force control of a parallel-series hybrid system," *JSAE Review*, vol. 20, no. 3, pp. 337-341, July 1999.

[8] V. Galdi, L. Ippolito, A. Piccolo, and A. Vaccaro, "A genetic-based methodology for hybrid electric vehicles sizing," *Soft Computing*, vol. 6, pp. 451-457, 2001.

[9] A. Sciarretta, M. Back, and L. Guzzella, "Optimal control of parallel hybrid electric vehicles," *IEEE Trans. on Control Systems Technology*, vol. 12, no. 3, pp. 352-363, May 2004.

[10] C. A. Coello Coello, D. A. Van Veldhuizen, and G. B. Lamont, *Evolutionary Algorithms for Solving Multi-Objective Problems*, Springer, 2007.

[11] K. Deb, *Multi-Objective Optimization Using Evolutionary Algorithms*, Wiley, 2001.

[12] D. Assanis, G. Delagrammatikas, R. Fellini, Z. Filipi, J. Liedtke, N. Michelena, P. Papalambros, D. Reyes, D. Rosenbaum, A. Sales, and M. Sasena, "An optimization approach to hybrid electric propulsion system design," *Mechanics Based Design of Structures and Machines*, vol. 27 no. 4, pp. 393-421, 1999.

[13] S. Fish and T. B. Savoie, "Simulation-based optimal sizing of hybrid electric vehicle components for specific combat missions," *IEEE Trans. on Magnetics*, vol. 37, no. 1, pp. 485-488, Jan. 2001.

[14] R. Fellini, N. Michelena, P. Papalambros, and M. Sasena, "Optimal design of automotive hybrid powertrain systems," in *Proc. of Environmentally Conscious Design and Inverse Manufacturing*, Tokyo, Japan, Feb. 1999, pp.400-405.

[15] K. Wipke, T. Markel, and D. Nelson, "Optimizing energy management strategy and degree of hybridization for a hydrogen fuel cell SUV," in *Proc. 18th Electric Vehicle Symposium*, Berlin, Germany, 2001.

[16] D. R. Jones, "DIRECT global optimization algorithm," *Encyclopaedia of Optimization*, Kluwer Academic Publishers, 2001.

[17] P. Caratozzolo, M. Serra, and J. Riera, "Energy management strategies for hybrid electric vehicles," in Proc. *IEEE International Electric Machines and Drives Conf.*, Madison, WI, June 2003, vol. 1, pp. 241-248.

[18] C. C. Lin, H. Peng, J. W. Grizzle, and J. M. Kang, "Power management strategy for a parallel hybrid electric truck," *IEEE Trans. on Control Systems Technology*, vol. 11, no. 6, pp. 839-849, Nov. 2003.

[19] B. M. Baumann, G. Washington, B. C. Glenn, and G. Rizzoni, "Mechatronic design and control of hybrid electric vehicles," *IEEE Trans. on Mechatronics*, vol. 5, no. 1, pp. 58-71, March 2000.

[20] National Renewable Energy Laboratory, "Advanced vehicle simulator (ADVISOR) documentation," see: http://www.ctts.nrel.gov.

[21] L. Wang, *A Course in Fuzzy Systems and Control*, Upper Saddle River, NJ, 1997.

[22] G. Shi, Y. Jing, A. Xu, and J. Ma, "Study and simulation of based-fuzzy-logic parallel hybrid electric vehicles control strategy," in *Proc. IEEE International Conf. on Intelligent Systems Design and Applications*, Jinan, China, Oct. 2006, vol. 1, pp. 280-284.

[23] H. D. Lee and S. K. Sul, "Fuzzy-logic-based torque control strategy for parallel-type hybrid electric vehicle," *IEEE Trans. on Industrial Electronics*, vol. 45, no. 4, pp. 625-632, Aug. 1998.

[24] C. Y. You, W. Y. Park, G. M. Jeong, C. Moon, and H. S. Ahn, "A comparative study of fuzzy logic-based control strategies for a parallel mild hybrid electric vehicle," in *Proc. IEEE International Conf. on Control, Automation and Systems*, Seoul, Korea, Oct. 2008, pp. 1042-1046.

[25] A. Rajagopalan, G. Washington, G. Rizzoni, and Y. Guezennec, "Development of fuzzy logic control and advanced emissions modeling for parallel hybrid vehicles," NREL/SR-540-32919, Dec. 2003.

[26] Y. Zhu, Y. Chen, G. Tian, H. Wu, and Q. Chen, "A four-step method to design an energy management strategy for hybrid vehicles," in *Proc. IEEE American Control Conf.*, Boston, MA, June 2004, pp. 156-161.

[27] E. D. Tate and S. P. Boyd, "Finding ultimate limits of performance for hybrid electric vehicles," in *Proc. SAE Future Transportation Technology Conf.*, Paper No. 00FTT-50.

[28] C. C Lin, H. Peng, J. W. Grizzle, J. M Kang "Power Management Strategy for a Parallel Hybrid Electric Truck," *IEEE Trans. on Control Systems Technology*, vol. 11, no. 6, pp. 839-849, Nov. 2006.

[29] L. C. Fang and S. Y. Qin, "Concurrent optimization for parameters of powertrain and control system of hybrid electric vehicle based on multi-objective genetic algorithms," in *Proc. IEEE International Joint Conf. SICE-ICASE*, Busan, Korea, Oct. 2006, pp. 2424-2429.

[30] A. Piccolo, L. Ippolito, V. zo Galdi, and A. Vaccaro, "Optimisation of energy flow management in hybrid electric vehicles via genetic algorithms," in *Proc. IEEE International Conf. on Advanced Intelligent Mechatronics*, Corno, Italy, July 2001, vol. 1, pp. 434-439.

[31] J. S. Won, R. Langari, and M. Ehsani, "An energy management and charge sustaining strategy for a parallel hybrid vehicle with CVT," *IEEE Trans. on Control Systems Technology*, vol. 13, no. 2, pp. 313-320, March 2005.

[32] M. Jain, C. Desai, N. Kharma, and S. S. Williamson, "Optimal powertrain component sizing of a fuel cell plug-in hybrid electric vehicle using multi-objective genetic algorithm," in *Proc. IEEE Annual Conf. of the Industrial Electronics Society*, Porto, Portugal, Nov. 2009, pp. 3741-3746.

[33] C. Desai and S. S. Williamson, "Optimal design of a parallel hybrid electric vehicle using multi-objective genetic algorithms," in *Proc. IEEE Vehicle Power and Propulsion Conf.,* Dearborn, MI, Sept. 2009, pp. 871-876.

[34] C. Musarado, G. Rizzoni, and B. Staccia, "A-ECMS: an adaptive algorithm for hybrid electric vehicle energy management," in *Proc. IEEE Conf. on Decision and Control*, Seville, Spain, Dec. 2005, pp. 1816-1823.

[35] G. Paganelli, S. Delpart, T. M. Guerra, J. Rimaux, and J. J. Santin, "Equivalent consumption minimization strategy for parallel hybrid powertrains," in *Proc. IEEE Vehicular Technology Conf.*, Birmingham, AL, May 2002, pp. 2076-2080.

[36] A. Sciarretta, M. Back, and L. Guzzella, "Optimal control of parallel hybrid electric vehicles," *IEEE Trans. on Control Systems Technology*, vol. 12, no. 3, pp. 352-363, May 2004.

[37] M. Salman, M. F. Chang, and J. S. Chen, "Predictive energy management strategies for hybrid vehicles," in *Proc. IEEE Conf. on Decision and Control*, Seville, Spain, Dec. 2005, pp. 21-25.

[38] C. Desai and S. S. Williamson, "Comparative study of hybrid electric vehicle control strategies for improved drivetrain efficiency analysis," in *Proc. IEEE Electrical Power and Energy Conference Conf.,* Montreal, QC, Oct. 2009, pp. 1-6.

[39] N. Srinivas and K. Deb, "Multiobjective optimization using non-dominated sorting genetic algorithms," *Journal of Evolutionary Computation*, vol. 2, no. 3, pp 221-248, 1994.

[40] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm, NSGA-II," *IEEE Trans. on Evolutionary Computation*, vol. 6, no. 2, pp 182-197, April 2002.

[41] E. Zitzler, K. Deb, and L. Thiele, “Comparison of multiobjective evolutionary algorithms: Empirical results,” *Evolutionary Computation Journal*, vol. 8, no. 2, pp. 125-148, 2000.

[42] J. Knowles and D. Corne, “The Pareto archived evolution strategy: a new baseline algorithm for multiobjective optimization,” in *Proc. IEEE Congress on Evolutionary Computation*, Washington, D. C., July 1999, pp. 98-105.

[43] E. Zitzler and L. Thiele, “Multiobjective optimization using evolutionary algorithms: a comparative case study and the strength Pareto approach,” *IEEE Trans. on Evolutionary Computation*, vol. 3, no. 4, pp. 257-271, Nov. 1999.

[44] K. Deb, “Multi-objective genetic algorithms: problem difficulties and construction of test Functions,” *Evolutionary Computation*, vol. 7, no. 3, pp 205-230, 1999.

[45] M. S. Manas, “Graphical methods of multi-criterion optimization,” *Zeitschrift fur Angewandte Methematic und Mechanik,* vol. 62, no. 5, pp 375-377, 1982.

[46] T. Markel, “Platform engineering applied to plug-in hybrid electric vehicles,” in *Proc. SAE World Congress*, Detroit, MI, April 2007, Paper No. 2007-01-0292.

[47] C. Desai, M. Jain, and S. S. Williamson, “Genetic algorithm based optimal powertrain component sizing and control strategy design for a fuel cell hybrid electric bus,” in *Proc. IEEE Vehicle Power and Propulsion Conf.,* Dearborn, MI, Sept. 2009, pp. 980-985.

[48] T. Markel and A. Simpson, “Plug-in hybrid electric vehicle energy storage system design,” in *Proc. Advanced Automotive Battery Conf.*, Baltimore, MD, May 2006, NREL/CP-540-39614.

[49] Matlab Stateflow user guide, see www.mathworks.com.

[50] D. Harel, "Statecharts: A Visual Formalism for Complex Systems," *Science of Computer Programming*, vol. 8, pp. 231–274, 1987.