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ENERGY OPTIMAL OPERATION OF ELECTRIC TRAINS

DEVELOPMENT OF A DRIVER ADVISORY SYSTEM

Nima Ghaviha

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MÄLARDALEN UNIVERSITY
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School of Business, Society and Engineering

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Abstract

The electric traction system used in trains is the most energy efficient traction system in the transportation sector. Moreover, it has the least NO_x and CO_2 emissions in comparison to other transportation systems (e.g. busses, passenger cars, airplanes, etc.). On the other hand, they are extremely expensive, mainly due to high installation and maintenance cost of the catenary system, including e.g. overhead lines and substations. Consequently, the share of electrified lines is only slightly higher than non-electrified lines. For instance in Europe, 60% of the railway networks are electrified, and the percentage is much lower in other continents. Battery driven trains are a new generation of electric trains that can overcome such high costs while keeping CO_2 emissions and energy consumption low. At the moment, there are only two battery driven electric trains developed and both of the trains are passenger electric multiple units (EMUs). An EMU is an electric train with a traction system in more than one wagon, in contrast to loco-haul electric trains which have a traction system in one wagon only. Energy management during the operation of battery driven trains is a crucial task, as energy optimal operation of trains considering the optimal use of batteries can increase both the operating time and the lifetime of batteries. Energy efficient train operation is realized using driver advisory systems (DAS) that instructs drivers on how to drive trains for minimum energy consumption. The aim of this research is to propose an algorithm for speed profile optimization of both EMUs and battery driven EMUs. The desired algorithm should be suitable as a core component for an online DAS with short response time. Several approaches are proposed in the literature for speed profile optimization of electric trains, and a few of these have been proposed for speed profile optimization of battery driven electric trains. The trains modeled in almost all of the approaches are trains using a notch system for controlling tractive effort. The proposed solution in this research project is to use discrete dynamic programming (DP) to find the optimum speed profile. The application of DP is studied for speed profile optimization of EMUs with a notch system as well as EMUs with a smooth gliding handle for controlling tractive effort. The problem is solved for both normal EMUs and battery driven EMUs. The results of this research show that DP can provide accurate results in a reasonably short time. Moreover, the proposed algorithm can be used as a base for a DAS with fast response time (real-time).

Sammanfattning

Elektriska traktionssystem i tåg är det mest energieffektiva alternativet inom transportsektorn, och dessutom har det lägst NO_x- och CO_2-utsläpp i jämförelse med andra transportsystem (exempelvis bussar, personbilar, flygplan, etc.). andra sidan är de relativt dyra, främst på grund av höga installations- och underhållskostnader för kontaktledningssystem, inklusive t.ex. luftledningar och transformatorstationer. Följaktligen är andelen elektrifierade linjer något högre än andelen icke-elektrifierade linjer. I Europa är endast 60 % av järnvägsnäten elektrifierade, och andelen är till och med mycket lägre i andra världsdelar. Batteridrivna tåg representerar en ny generation av eltåg som kan nå rimliga kostnader samtidigt med låga CO2-utsläpp och låg energiförbrukning. För närvarande finns det bara två batteridrivna elektriska tåg utvecklade och båda tågen är passagerartåg med elektriska multipla enheter (EMUs). En EMU är ett elektriskt tåg med drivsystem i mer än en vagn, i motsats till lokomotiveltåg som har framdrivningssystemet centrerat till en enda vagn. Energihantering under driften av batteridrivna tåg är en viktig uppgift, och vid en energioptimal drift av tåget tillsammans med en optimerad användning av batterier ökar både driftstiden och livscykeln för batterierna. Energioptimal drift tillämpas i tågdrift med hjälp av ett system som kallas förarrådgivning (eng. Driver Advisory Support, DAS). DAS är ett system som instruerar tågföraren om hur man kör tåget med minimal energiförbrukning. Syftet med denna forskning är att föreslå en algoritm för hastighetsprofilsoptimering av både vanliga EMU:er samt motsvarande batteridrivna. Den önskade algoritmen skall vara lämpad att användas som en bas fr ett online-DAS med kort svarstid. Olika metoder föreslås i litteraturen fr hastighetsprofilsoptimering av eltåg, och några även för hastighetsprofilsoptimering av batteridrivna elektriska tåg. De tågmodeller som används har oftast ett så kallat notch-system fr kontrollering av dragkraft. Den föreslagna lösningen i detta forskningsprojekt r att använda diskret dynamisk programmering (DP) för att hitta den optimala hastighetsprofilen. Tillämpning av DP studeras fr hastighetsprofilsoptimering av EMU:er både med notch-system samt EMU:er med ett kontinuerligt glidhandtag för styrning av dragkraft. Problemet löses fr både normala EMU:er och batteridrivna EMU:er. Resultaten av denna forskning visar att DP kan ge korrekta resultat inom rimlig tid. Vidare kan den föreslagna algoritmen användas som en bas för en DAS med snabb svarstid (realtid).

To my Family

Acknowledgment

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Nima Ghaviha
Västerås, May, 2016

List of Papers

- **Paper A :** *Optimal Control of an EMU Using Dynamic Programming.* Nima Ghaviha, Markus Bohlin, Fredrik Wallin, Erik Dahlquist, Energy Procedia, Clean, Efficient and Affordable Energy for a Sustainable Future: The 7th International Conference on Applied Energy (ICAE2015)
- **Paper B :** *Optimal Control of an EMU Using Dynamic Programming and Tractive Effort as the Control Variable.* Nima Ghaviha, Markus Bohlin, Fredrik Wallin, Erik Dahlquist, Proceedings of the 56th SIMS October 07-09, 2015, Linköping, Sweden
- **Paper C :** *Flow batteries use potential in heavy vehicles.*, Javier Campillo, Nima Ghaviha, Nathan Zimmerman, Erik Dahlquist, 2015 International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles, ESARS 2015 (*IEEE*),
- **Paper D :** *Speed Profile Optimization of an Electric Trains with Onboard Energy Storage and Continuous Tractive Effort*, Nima Ghaviha, Markus Bohlin, Erik Dahlquist, 23rd International Symposium on Power Electronics, Electrical Drives, Automation and Motion, SPEEDAM 2016 (*IEEE*) - *accepted for publication*

Related Publications not Included in the Thesis

- *Algorithm for the Optimal Control of an Electric Multiple Unit.* Nima Ghaviha, Markus Bohlin, Fredrik Wallin, Erik Dahlquist, 55th SIMS Conference on Simulation and Modelling, SIMS 2014, October 21 to 22, 2014, Aalborg, Denmark
- *Joint Optimization of Multiple Train Speed Profiles.* Ariona Shashaj, Markus Bohlin, Nima Ghaviha, 6th International Conference on Power Engineering, Energy and Electrical Drives, 10th International Conference on Compatibility and Power Electronics, CPE-PowerEng 2014 (*IEEE*) - *accepted for publication*

Contents

Nomenclature

A	Constant for running resistance $[N]$
B	Constant for running resistance $[N/(km/h)]$
b_{max}	total number of discretization steps for battery level or state of charge
C	Constant for running resistance $[N/(km/h)^2]$
F_g	Gradient Force$[N]$
F_t	Tractive effort $[N]$
F_{rr}	Running Resistance $[N]$
$g_k(x_k, u_k)$	transition cost
I	Current in DC Link$[A]$
$J_\pi(x_k)$	cost-to-go for state x_k, when applying series of control variables π
m	Train mass $[kg]$
P_{aux}	Power consumption of auxiliary systems$[kW]$
s_{max}	total number of discretization steps for distance
t_{max}	total number of discretization steps for time
u_k	decision or control variable
V	Voltage of DC Link$[V]$

v	Train velocity $[km/h]$
v_{max}	total number of discretization steps for velocity
x_k	state variable

Abbreviations

AC	Alternative Current
ACM	Auxiliary Converter Module
DAS	Driver Advisory System
DC	Direct Current
DP	Dynamic Programming
EMU	Electric Multiple Unit
LCM	Line Converter Module
MCM	Motor Converter Module
MVA	Mega-Volt Ampere

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I

Thesis

Chapter 1

Introduction

Railway transportation is one of the most energy efficient and environmentally friendly means of transportation. According to a report by International Energy Agency and International Union of Railways [1], 23.1% of global CO2 emissions are produced by transport sector, out of which 3.6% is produced by railways transportation. This is considering the fact that since 1990 global CO2 emissions has increased by 50%, while the share of railway transportation has been dropping [1].

Railway transportation is also ahead of other transportation means in terms of energy consumption. A typical loco-hauled electric train or high speed train with 40% load factor consumes $0.1\,\mathrm{kWh/passenger-km}$, while a long distance bus for instance consumes $0.2\,\mathrm{kWh/passenger-km}$ and a turboprop aircraft with 60% load factor consumes $0.6\,\mathrm{kWh/passenger-km}$ [2].

Considering emissions and energy consumption figures, together with the fact that railway has 8% share of total transportation (goods and passengers), implies that railway is one of most green transportation systems [1].

The electric traction system and the trend of railway electrification are responsible for most of the decrease in CO2 emissions and reduction of energy consumption [3]. In total around 30% of all railway lines in the world are electrified. In Europe, however, 60% of railway lines are electrified [1]. Nonetheless, the global trend shows that railway industry is moving towards the electric traction system rather than fuel based motors as the main traction system [1]. As a result there is an increasing need to improve efficiency of such systems.

1.1 Background and motivation

The electric traction system is the most energy efficient system in the railway industry. This is mainly due to low running resistance, high efficiency and the regenerative brake system, which converts kinetic energy to electrical energy. At the same time electric trains consume huge amounts of energy. Railway sector consumed a total of 2200 PJ in 2012 [1].

There is still a need for improvement as new environmental and energy efficiency regulations (e.g. EU 2020 goals) are calling for more CO2 reduction and increases in energy efficiency. Improvement in railway sector can be achieved in two categories: more energy efficient train unit and energy efficient train unit operation. This thesis considers energy efficient train unit operation, with the focus on energy efficient speed profile optimization and development of a driver advisory system. The issue is studied for both normal electric trains, as well as a relatively new concept called battery driven trains.

One of the major challenges when dealing with electric traction system for trains is high setup and maintenance cost of infrastructure needed for electric trains. According to Baumgartner[4], investment capital needed for installation of an AC catenary system with a maximum speed limitation of $300\,\mathrm{km\,h^{-1}}$ is $0.2 \times 10^6 \mathrm{EUR/km}$. Added to this figure will be investment cost for substations (around $0.3 \times 10^6 \mathrm{EUR/MVA}$) and investment cost for signaling which is around $0.05 \times 10^6 \mathrm{EUR/km}$ for lines with low utilization and $0.1 \times 10^6 \mathrm{EUR/km}$ for lines with high utilization. There is also a maintenance cost which is 2% and 4% of yearly investment for catenary and signaling system respectively. Due to these high costs, electrification is not always a financially feasible alternative. Moreover, due to spacial limitations and safety issues, catenary system and overhead lines can not be installed everywhere (e.g. harbors and some residential areas). In these cases battery driven trains can be used. Energy management of such trains can improve the performance of batteries and also increase the operation time.

1.2 Objectives and Problem Description

Objective of this thesis is to find an energy optimum speed profile for a certain electric train configuration on a specific track section with a specific travel time. In other words, travel time and distance are constant. The electric train addressed in this thesis has a gliding handle for controlling tractive effort, much like the accelerator pedal in cars, in contrast to notch system, which allows the driver to choose between a certain number of discrete levels on the throttle controller to control the applied tractive effort (usually 8 levels or notches). The results from speed profile optimization will be used later on as a base for a driver advisory system (DAS). This means that it should be possible to give instructions to the driver in a relatively short time during a trip to minimize total energy consumption.

The same problem will be addressed for catenary-free operation of battery driven electric trains, where there are limitations both on the amount of energy that can be consumed and on the amount of energy restored using the regenerative brake system.

1.3 Delimitations

The focus of the research described in this thesis is on electric multiple units (EMU), which are electric trains with more than one propulsion system in different wagons. These type of trains are equipped with regenerative brakes, that generate electrical energy from kinetic energy. Mechanical brakes are also available in these trains, but they are not used except in emergencies or at low speed. Moreover the EMUs modeled in this thesis are used as passenger trains for intercity applications, although it is possible to adjust the solution for other purposes as long as the train model stays the same.

Propulsion system in trains consist of different components, each having a certain efficiency in terms of energy consumption. In real application loss of each component is a function of velocity and tractive effort, however in the train modeled in this thesis, the efficiency of the whole propulsion system is represented by an overall coefficient. More specifically, the coefficient accounts for all the losses from the DC link to wheels, including losses in the motor converter module (MCM), auxiliary converter module (ACM), motor and gear box.

The problem is solved for a single train operation, meaning that interaction between two trains or more is not considered in this thesis. When considering the regenerative brake system, it is assumed that there is always enough capacity on grid to receive energy input from the regenerative brake system. In other words, there is always another train accelerating elsewhere that can use the surplus of energy generated from the braking train, or there are stationary energy storage devices connected to the grid that can store the energy surplus for future use.

The problem is solved for a single energy source, which is either the overhead line or an energy storage device (i.e. a battery). The problem can also be formulated for multiple energy sources as there are trains that use a secondary energy storage device (mostly a supercapacitor) to increase efficiency of the regenerative brake system ([5] and [6]). This is however, not in the scope of this research project.

1.4 Outline of thesis

This thesis consists of 7 chapters and the outline will be as follows:

Chapter 2 will focus on the literature review of current solutions and a study on the available driver advisory systems in the markets. Included is also a study on application of energy storage devices in trains and the need for battery driven trains. As the result of the literature review, current knowledge gaps are found.

Based on the current knowledge gaps introduced in chapter 2, research questions are defined in chapter 3, followed by the methodology used to answer each question. The methodology also includes the configuration of the EMU which is used as case study in this thesis together with its mathematical modeling. Moreover, a short introduction to the optimization technique and its application to this specific problem is discussed.

An overview of included papers is presented in chapter 4 together with the relation between research questions and papers.

Results and discussions are presented in chapter 5. The results are divided into the two subsections of results for normal EMUs and battery driven EMUs. Chapter 5 concludes with the contribution of the thesis based on the results.

The over all conclusion of the thesis is presented in chapter 6. Finally, the thesis concludes with future work in chapter 7

Chapter 2

Literature Review

The problem of energy efficient train operation has been studied for many decades, and different solutions have been offered for different train configurations. In terms of application, suggested solutions can be divided in three categories of single train operation, operation with energy storage device and multiple train operation. As the focus of this thesis is on electric multiple units, the literature review only addresses previous research in the three mentioned categories for electric multiple units. Generally speaking, the problem for each category can be solved with two main approaches: solving the problem as a dynamic optimization problem, and as a coast control problem. In coast control, the problem is to find the optimum coasting speed(s) for the whole trip or different line sections. Each speed profile consists of 3 main driving modes which are acceleration, constant speed, coasting and braking. Coasting is the mode in which no tractive effort is taken from the propulsion system, meaning that the only source of energy consumption is auxiliary systems. The result of coast control problem consists of full acceleration sections, coasting sections and full braking sections. In dynamic optimization however, the optimum speed profile is sought for the whole trip, regardless of driving mode. In spite of this, the result still includes coasting mode, as in coasting mode, the train consumes no energy and moves as a result of its current kinetic energy.

2.1 Single Train Operation

In single train operation the problem is solved for one train only and interaction between the train and other trains in network or substations are not considered. The very first work in this field was done by Ichikawa [7], who saw the problem as an optimal control problem. The main approaches used to solve the problem for a single train are dynamic programming (see e.g. [8]), sequential quadratic programming, maximum principle (see e.g. [9, 10, 11, 12]) and gradient method.

The problem has also been solved as a coast control problem. Genetic algorithm and evolutionary algorithm based solutions are the most used approaches to solve the coast control problem (see e.g. [13, 14, 15, 16]). Other techniques such as artificial neural networks ([17]), heuristic searching methods([18]) and ant colony optimization are also proposed in the literature ([19]).

2.2 Operation with Energy Storage Device

One of the main advantages of electric trains is the use of a regenerative brake system which converts kinetic energy to electrical energy. In other words, electric trains can generate electricity while braking. In an ideal situation, regenerated energy can be sent back to the line to be used by other trains which are accelerating at the exact same moment. However, this might not happen in real applications, as planning trains to synchronise like this would be a very complex problem. Moreover, it is desirable to use regenerated energy on the same train as transmitting energy to another train using the grid would result in increased losses. Thus, to get the best use out of the regenerative brake system, many modern electric train are equipped with an on-board energy storage device such as batteries or super capacitors to store the regenerated energy for use in acceleration mode.

Energy storage devices are also used as the sole energy source for some electric trains. High installation and maintenance cost of the catenary system makes it economically unfeasible to have standard electric trains on routes with low utilization. Battery driven trains make it possible to get maximise use of braking energy while avoiding the high costs of overhead lines. Such trains need high capacity batteries that can also provide high peak power. Currently two battery driven electric multiple units have been developed, both using lithium-ion batteries. As trains have such high energy consumption (peak power can be in the order of megawatts), energy management of battery driven trains is of high importance to get the best use out of batteries.

An on-board energy storage device adds a new constraint to the problem of speed profile optimization, as there will be a limited secondary energy source outside the catenary system. Four main approaches are mentioned in the literature to tackle the new problem: sequential quadratic programming, dynamic programming and gradient-based methods for dynamic optimization and particle swarm optimization for coast control. Miyatake found the optimal speed profile for electric trains with an on-board energy storage device (a supercapacitor in this case) using sequential quadratic programming ([6, 20]). Application of dynamic programming was also studied by Miyatake for speed profile optimization of catenary free operation of electric trains with an on-board energy storage device ([21, 22]). The gradient method has also been studied for operation of an EMU under a DC feeding circuit, i.e. a supercapacitor ([23]).

The coast control problem has also been presented and solved using particle swarm optimization for catenary-free operation of EMUs with an on-board energy storage device [24].

2.3 Multiple Train Operation

As previously mentioned, one way to use regenerated energy from the regenerative brake system is to send it back to the line for use by another train. In the multiple train operation problem, the objective is minimization of the total energy consumption of multiple trains. Alternatively the problem can be framed as minimizing the total energy consumption of a substation. The coast control problem can also be defined for multiple train operation. Genetic algorithm, artificial neural network and simulation technique have been used to solve the coast control problem for multiple train operation [25, 26].

In addition, dynamic programming [27] and a gradient based method have been used to solve the problem as a dynamic optimization problem. Miyatake and Ko used the gradient method to propose a solution for a problem with multiple train operation and solved the problem for two trains. Dynamic programming is also proposed to be used for solving the problem for two trains [27].

2.4 Driver Advisory System

In order to use the results of speed profile optimization on a real train, it should be implemented in the form of a driver advisory system (DAS). DAS is a system which instructs drivers on how to drive a train. The goal of a DAS can be minimizing energy consumption or time managing. Many DAS systems are available on the market, but little is known regarding the mathematical basis behind the systems. The most comprehensive study of available DAS systems in the market is presented by Panou et al [28].

2.5 Knowledge Gaps

In summary a list of optimization techniques used for both coast control and speed profile optimization is shown in figure 2.1.

A review of related works identifies the following gaps in the literature:

- Continuous Tractive Effort

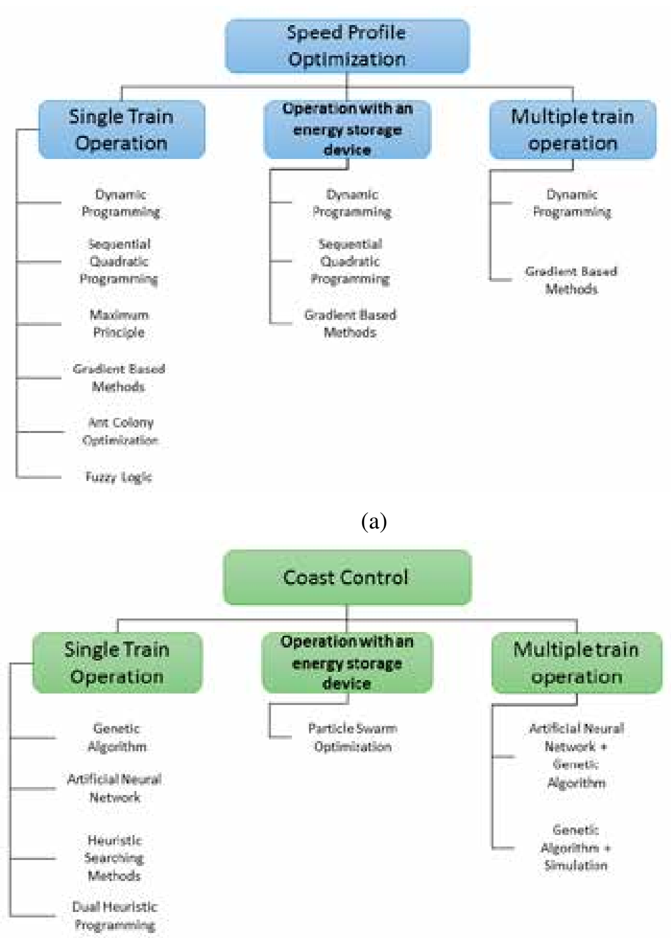
  Almost all the trains modeled in the literature are equipped with a number of notches to control tractive effort. However some trains are equipped with a smooth gliding handle for the control of tractive effort. The only exception is presented by Howlett for diesel-electric trains [29].

- Battery Driven Trains

  Although much work has been performed on speed profile optimization of electric trains with on-board energy storage devices, there has not been much work on electric trains with only batteries as the energy source. The most significant work in this field is done by Miyatake for battery driven trains with tractive effort as control variable.

- Driver Advisory System

  Many driver advisory systems have been developed and are available on the market. However little has been published on the mathematical basis of the systems. The most comprehensively described driver advisory system is called Freightmeiser and Energymeiser (see [29, 30, 31, 32, 33])



(a)

(b)

Figure 2.1: Approaches used for speed profile optimization (*a*) and coast control of electric trains (*b*)

Chapter 3

Research Framework

Research framework of the thesis is presented in this chapter, starting with defining the research questions. The research questions are defined based on the current knowledge gaps found in chapter 2 and the scope of the project presented in chapter 1. Following the research questions, the methodology to answer each research question is presented. The methodology section also includes the train configuration and model, together with an introduction to the optimization technique used in this thesis.

3.1 Research Questions

The problem of speed profile optimization of electric trains and in a more general context, trains, has been studied for several decades. Almost all of the solutions suggested are designed for trains with a certain number of levels for controlling tractive effort (i.e. notch system); the proposed approaches mostly use tractive effort as the decision variable. The same problem can also be studied for battery driven EMU's. Based on the current knowledge gaps, following research questions are set for this research:

- **RQ1** What is the status of application of energy storage devices in trains and what are the existing approaches for speed profile optimization of electric trains and battery driven electric trains?

- **RQ2** How efficient is dynamic programming when used for designing a DAS for EMU's with continuous tractive effort?

- **RQ3** How efficient is dynamic programming when used for designing a DAS for battery driven EMU's with continuous tractive effort?

3.2 Methodology

The work done in this thesis is applied and focuses on electric multiple units designed by Bombardier Transportation in Västerås. The research started with a literature review on the current existing approaches for speed profile optimization and application of energy storage devices in the railway industry to answer research question 1.

The second and third research questions are answered by further developing a mathematical model for normal EMU and developing a model for battery driven EMU based on real train and battery data acquired from Bombardier Transportation through meetings and documents. The optimization technique used is dynamic programming (DP) which is proved to be a global optimization technique suitable for optimization problems with low number of design variables [34]. Train models are validated regarding energy calculations using an in house software developed by Bombardier Transportation. In addition, the accuracy of the final results is evaluated using statistical error analysis of the results from a number of simulations.

The problem of speed profile optimization of electric trains can be seen as a cross section between energy engineering, operation research and power engineering. Therefore, data was gathered on electric trains and structure of train propulsion system through regular meetings with power engineers from Bombardier Transportation.

The research done in this thesis is based on the work previously presented by Gkortzas[35].

3.2.1 Train Configuration

Electric Multiple Units (EMU) are addressed in this thesis. Such trains, in contrast to trains with locomotives, have traction motors in more than one wagon. EMUs are mostly used as passenger trains and are relatively small compared to freight trains. The Electrostar EMU developed by Bombardier Transportation is a train modeled and used as case study in this thesis. Figure 3.1 represents a technical drawing of wagon from an Electrostar train[1].

[1] source: "http://www.bombardier.com/en/transportation/projects/project.electrostar-uk.html", retrieved on 28-04-2016

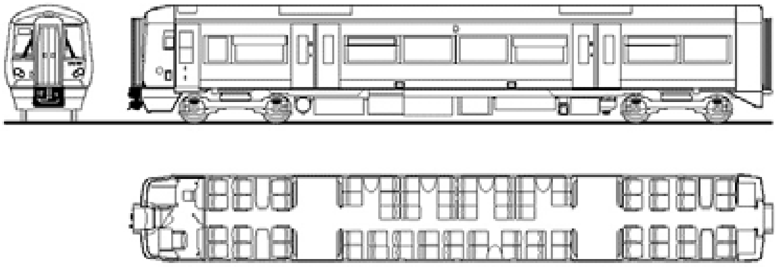


Figure 3.1: Technical drawing of a wagon from an Electrostar EMU operated in United Kingdom

There are usually 4 of such wagons (see figure 3.1) in an Electrostar EMU, from which 3 are equipped with a traction motor and the other one is a trailer wagon with no traction motor. Figures 3.2 and 3.3 represent a simple drawing of traction system in Electrostar EMUs and the same EMU equipped with batteries respectively. LCM, MCM and ACM blocks are line converter module(LCM), motor converter module(MCM) and auxiliary converter module(ACM) respectively. The first LCM and MCM blocks are for the motor and the second LCM block is intended for charging the batteries (Figure 3.3). Both LCMs are basically AC/DC converters and MCM is a DC/AC converter, as the train is equipped with an asynchronous three phase AC motor. The ACM consists of a DC/AC converter and also an AC/DC converter to provide auxiliary systems with both AC and DC power.

During operation under overhead lines, connections $C1$ and $C2$ are connected while $C3$ is disconnected (Figure 3.3), allowing batteries to be charged while simultaneously using electricity from overhead lines for driving the train. During catenary-free operation however, both $C1$ and $C2$ are disconnected and $C3$ is connected. Note that figures 3.2 and 3.3 are just schematic drawings to show the circuits. In real applications the order and layout of components is not the same. For instance, there is only one main transformer for all three traction systems in a four wagon EMU.

The length of a typical 4 wagon Electrostar EMU is around $20\,\mathrm{m}$ long, weighs around $184\,000\,\mathrm{kg}$ and can seat around 250 passengers.

A common way to control electric trains or trains in general, is through a notch system. In a notch system, the driver controls the train using a throttle controller with a number of levels on it. Each level corresponds to a certain

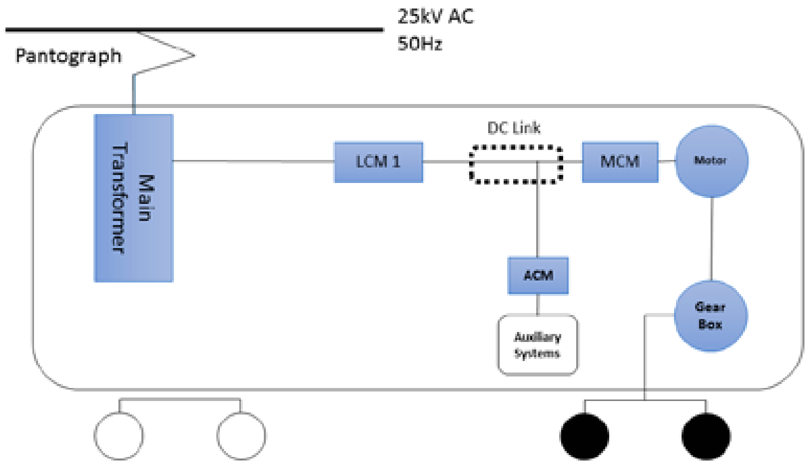


Figure 3.2: Electrostar EMU traction system

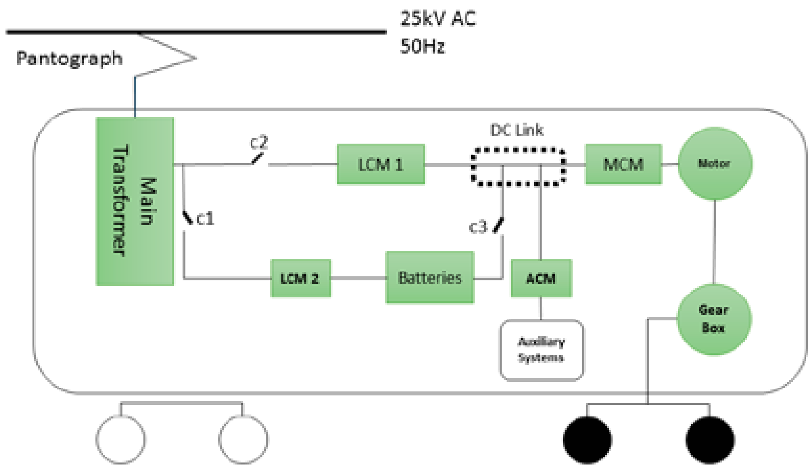


Figure 3.3: Electrostar EMU traction system equipped with batteries

percentage of tractive effort, meaning that the driver has access to discrete values of tractive effort. The number of throttle levels vary from train to train; a common number of levels is 8 (4 for acceleration, one for coasting and 3 for braking). The other way to control trains is using a gliding handle. In this system driver can apply any value of tractive effort from the traction system. In other words, the driver has access to continuous values of tractive effort. The focus in thesis is on trains with continuous tractive effort. Figure 3.4 shows values of tractive effort available at each velocity for the train modeled in this thesis, while figure 3.5 represents the same for the trains with a notch system for controlling tractive effort.

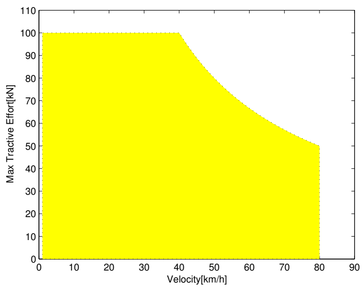


Figure 3.4: Amount of tractive effort available for the trains without notch system. All of the values are applicable.

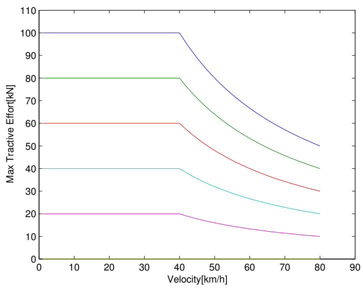


Figure 3.5: Amount of tractive effort available for the trains with notch system. Only the values on the lines are applicable.

Both the EMU and the battery driven EMU addressed in thesis use continuous tractive effort instead of the notch system.

3.2.2 Train Model

As the length of the train studied here is relatively short, it is modelled as a single mass point. The forces affecting the train, according to Ostlund [2], are as follows:

- Rolling resistance
- Aerodynamic resistance

- Curve resistance
- Gradient resistance
- Tractive effort

Curve resistance is assumed to be zero in this model. Rolling resistance and aerodynamic resistance (referred to collectively as running resistance, F_{rr}) are calculated using the Davis formula (equation 3.1) [36]. A, B and C are constants dependent on track and train and v is the speed of the train. The quadratic term in the Davis formula represents the aerodynamic force.

$$F_{rr} = A + B \times v + C \times v^2 \tag{3.1}$$

Gradient resistance (F_g) is calculated using equation 3.2, in which g is earth gravitational constant($9.8\,\mathrm{m\,s^{-2}}$), m is train mass in kg, α is angle of slope and κ is change in elevation for every $1000\,\mathrm{m}$ distance.

$$F_g = m \times g \times \sin(\alpha) = m \times g \times (\kappa/1000) \tag{3.2}$$

Denoting tractive effort (force from traction motor during both acceleration and braking) by F_t, the relationship between the forces is shown by equation 3.3, in which a is the acceleration rate of the train.

$$m \times a = F_t + F_{rr} + F_g \tag{3.3}$$

The coefficient(η) is assumed to take into account losses from the DC link to wheels (see figures 3.3 and 3.2), which can be applied to both normal EMU and battery driven EMU. Considering that only regenerative brakes are used (except at low speeds), power consumption can be calculated using equation 3.4, in which P represents the total power consumption and P_{aux} is power consumption of auxiliary systems. The Electrostar EMU modelled in this thesis has a constant auxiliary power consumption of $80\,\mathrm{kW}$.

$$P = \begin{cases} F_t \times v/\eta + P_{aux} & \text{if } F_t > 0, \\ \eta \times F_t \times v + P_{aux} & \text{otherwise.} \end{cases} \tag{3.4}$$

The power calculated in equation 3.4 is a mechanical power based on equations of motion which can also be interpreted as electrical power in the DC link, presented in equation 3.5. V represents voltage and I represents current in DC link.

$$P = V \times I \tag{3.5}$$

3.2.3 Introduction to Dynamic Programming

Dynamic programming is a technique used for speed profile optimization of both EMUs and battery driven EMUs.

Dynamic programming is an optimization technique that can be applied to a multistage decision problem. The result will be an optimum function rather than a point. According to Bertsekas[34], a discrete-time dynamic system can be formulated as follows:

$$x_{k+1} = f_k(x_k, u_k, w_k), \quad k = 0, 1, ..., N-1, \tag{3.6}$$

in which N is the number of stages in the horizon, x_k is the state of system at stage k, u_k is the decision or control variable and w_k represents random disturbances that may affect the system from outside. As there are no disturbances in the systems modelled in this thesis, w_k is ignored and hence the equation 3.6 can be rewritten as follows:

$$x_{k+1} = f_k(x_k, u_k), \quad k = 0, 1, ..., N-1, \tag{3.7}$$

Assuming π is a series of decision variables (i.e. $\pi = u_0, .., u_{N-1}$), the aim is to find π^*, which is the optimum series of control variables resulting in the minimum cost for the whole horizon. The cost denoted by $g_k(x_k, u_k)$ is cost at each stage when applying control variable u_k to state x_k. Considering equation 3.7, $g_k(x_k, u_k)$ is also called transition cost which is the cost at stage i. Cost-to-go for state x_k when applying the series of control variables π is defined using equation 3.8, in which $g_N(x_N)$ is cost of the final state in the horizon. It can be interpreted as cost of getting from state x_k to final state x_N when applying π. The objective is to find π^* which minimizes J (see equation 3.9).

$$J_\pi(x_k) = \sum_{i=k}^{N-1} g_i(x_i, u_i) + g_N(x_N) \tag{3.8}$$

$$J^*(x_k) = \min_{\pi} \sum_{i=k}^{N-1} g_i(x_i, u_i) + g_N(x_N) \tag{3.9}$$

Assuming that optimum cost-to-go for the last state in the horizon is known ($J_N^* = g_N(x_N)$), by backward iteration in the horizon and using equation 3.10, optimum decision variable (i.e. u_k^*) for all the states in all steps in the horizon can be found.

$$J^*(x_k) = \min_{u} g(x_k, u_k) + J^*(x_{k+1}) \tag{3.10}$$

Using results from backward iteration (i.e. u_k^* for each state) and by forward simulation in the horizon from state x_k using equation 3.7, the optimum series of decision variables (i.e. π^*), as well as the optimum series of states can be found. For more information on dynamic programming, see [34].

In the rest of the thesis, backward iteration is called offline calculation and forward simulation is called online calculation.

3.2.4 Application of DP

To apply DP to the problem of speed profile optimization of EMUs certain variables will be defined according to the description in section 3.2.3.

- Horizon (N)

  Horizon is assumed to be travel time (T).

- state variable (x_k)

  is defined using two variables of distance (s_k in number of distance steps) and velocity (v_k in number of velocity steps), and therefore $x_k = (s_k, v_k)$. In case of battery driven EMU, a third state variable of battery level or state of charge (b_k in number of battery level steps) is added. Considering the definition of state variable here, we can say that the train starts the trip from state $x_0 = (0, 0)$ for normal EMUs and $x_0 = (0, 0, 0)$ for battery driven EMUs. The last state in the trip is defined as $x_N = (s_{max}, 0)$ for normal EMUs and $x_N = (s_{max}, 0, b)$ for battery driven EMUs. s_{max} represents the maximum number of distance steps and b can be any value from zero to b_{max} which is the maximum number of battery level steps or state of charge.

- decision variable (u_k)

  is assumed to be velocity in the next stage or change in velocity. This is in contrast to other approaches that take notch number or tractive effort as the control variable.

- transition cost ($g_k(x_k, u_k)$)

  is defined as the amount of energy needed to drive the train in one time step, and can be calculated using equation 3.4.

- Cost-to-go ($J(x_k)$)

  is the amount of energy needed for driving the train from state x_k to the destination (x_N).

- $g_N(x_N)$

  Considering the definition of cost-to-go for and transition cost, in this problem, $g_N(x_N)$ is zero.

As presented in chapter 3.2.3, the optimum decision for all the states can be found by backward iteration in time (i.e. offline calculation). The total number of states for the problem with EMUs is $t_{max} \times s_{max} \times v_{max}$, each representing the maximum number of discretization steps for time, distance and velocity respectively. The total number of states for battery driven EMUs however, is equal to $t_{max} \times s_{max} \times v_{max} \times b_{max}$, where b_{max} is the total number of discretization steps for battery level. The optimum speed profile for the whole trip can be found by going forward in time from state x_0 using equation 3.7 and results from offline calculation (i.e. forward simulation or online calculation, see section 3.2.3). The same method can be used to find the optimum speed profile for any state during the trip (i.e. x_i).

Chapter 4

Overview of the Included Papers

In this chapter an overview of each included paper is presented. Furthermore, my contribution in each paper is also explained. The chapter ends with explaining the connections between all the papers.

- **Paper A:** *Optimal Control of an EMU Using Dynamic Programming.* Nima Ghaviha, Markus Bohlin, Fredrik Wallin, Erik Dahlquist

  The application of DP with velocity as control variable for speed profile optimization of EMUs was first presented by Gkortzas [35] for level tracks with no local speed limits. In paper A the model is further developed by adding gradient force, local speed limits and power consumption of auxiliary systems. Moreover the model is validated regarding the energy calculations. Validation is done against an in-house energy calculation software developed and being used at Bombardier Transportation called TEP. Furthermore, the application of the approach for an online DAS is studied. This is done in three areas of response time, accuracy of the results and the effects of discretization on coasting mode. The accuracy is studied by introducing an error resulting from discretization. Moreover, this paper discusses the effect of increasing trip time on reduction of energy consumption.

  The results of this paper show that the application of DP with velocity as the control variable is suitable for development of an online DAS for EMUs with continuous tractive effort.

I was the main author of this paper and performed the validations and all the experiments and simulations as well as studies on the accuracy, with the help and under supervision of my supervisors.

- **Paper B:** *Optimal Control of an EMU Using Dynamic Programming and Tractive Effort as the Control Variable.* Nima Ghaviha, Markus Bohlin, Fredrik Wallin, Erik Dahlquist

  DP has been used in literature for speed profile optimization of trains. As mentioned in the literature review, in most of the applications, tractive effort was used as control variable and trains modeled are mostly equipped with a throttle controller which has a number of levels for controlling tractive effort. In this paper, the two DP approaches of velocity and tractive effort as control variable were compared to find the better approach for the speed profile optimization of EMUs with no levels on throttle for controlling the tractive effort (Continuous tractive effort). For this purpose a same train model is used in both approaches in the same condition (i.e. same train and track data and also the same number of control and state variables) and the same accuracy presented in paper A is studied for both approaches. The results of this paper show that for speed profile optimization of EMUs with continuous tractive effort, DP with velocity as control variable performs better compared to DP with tractive effort as control variable.

  I was the main author of this paper and performed all the simulations and experiments, as well as studies on the accuracy, with the help and under supervision of my supervisors.

- **Paper C:** *Flow batteries use potential in heavy vehicles.*, Javier Campillo, Nima Ghaviha, Nathan Zimmerman, Erik Dahlquist

  This paper discusses the application of flow batteries in heavy vehicles including electric trains. The paper includes a feasibility study of flow batteries for construction equipment using energy consumption profiles of different operation tasks. I was the second author in this paper and my contribution in this paper was the whole section on railway transportation. It includes the statues of application of energy storage devices in trains and battery driven EMUs. In addition, my contribution also includes a short discussion on challenges regarding the application of energy storage devices as the sole energy source in EMUs. The discussion on challenges regarding the application of energy storage devices and also the status of application of battery driven EMUs was done based on the literature review of the related works. In addition, based on the discussion on the challenges, the possibilities of using flow batteries for different applications in railway sector is discussed.

- **Paper D:** *Speed Profile Optimization of an Electric Trains with Onboard Energy Storage and Continuous Tractive Effort*, Nima Ghaviha, Markus Bohlin, Erik Dahlquist

  This paper starts with a study on state of application of catenary-free operation of battery driven EMUs together with a comprehensive literature review on speed profile optimization of such trains. The paper continues afterwards with a solution to the problem of speed profile optimization of battery driven EMU with continuous tractive effort. This is done with the help of the same train model presented in previous papers. Having batteries as the sole energy source adds new constraints to the optimization problem. The new constraints regarding the batteries (e.g. state of charge) are handled with the introduction of a new state variable of battery level. This variable has different discrete values for different states of charge. Furthermore, the application of the solution for an online DAS is evaluated regarding the response time and the accuracy of the results. Accuracy is studied using the same kind of error introduced in paper A, as well as a new error on the new state variable. The two aspects of accuracy and response time are later on evaluated for a trip, using real EMU (Electrostar EMU) and track data (a line section in UK). Moreover, electrical equations needed to apply some of the constraints regarding the batteries are also added in this paper. This paper also includes a study on environmental effects of using battery driven EMUs instead of diesel multiple units.

  Results of this paper show that DP with velocity as control can be used for developing an online DAS for battery driven EMUs with short response time.

  I was the main author of this paper and performed all the experiments, modeling, simulations as well as studies on the accuracy, with the help and under supervision of my supervisors (except the study on environmental impacts of battery driven EMUs).

In summary, the papers and the corresponding research questions are listed in table 4.1

The publications presented in this thesis can also be categorized in three categories based on the targeted publisher. The problem of optimal operation

Paper	*Research Question*
Paper A	RQ 1 & 2
Paper B	RQ 1 & 2
Paper C	RQ 1
Paper D	RQ 1 & 3

Table 4.1: Research questions answered in each paper

of electric trains has three aspects: Modeling and Optimization, Energy Management, and Power Engineering. Based on these three categories, three type of publishers have been targeted. SIMS conference (paper B) cover the modeling and optimization aspect, whereas IEEE conferences (papers C and D) cover the electrical engineering aspect and the ICAE conference (paper A) covers the energy side of the problem.

Chapter 5

Results and Discussion

The focus of this thesis is on speed profile optimization and energy optimal operation of EMUs and battery driven EMUs. Therefore, results can be divided into two sections, for EMUs and for battery driven EMUs. The chapter concludes with the contribution of this thesis, which is in the form of the answers to each research question based on the presented results.

5.1 Speed Profile Optimization and Energy Optimal Operation of EMUs

Papers A and B deal with the problem for normal EMUs. The problem of speed profile optimization of EMUs with continuous tractive effort can be solved in two ways when using dynamic programming. The most common way is the same as the approach used for solving such problems for trains with the notch system. In the cases with trains with notch system, throttle level or tractive effort is usually used as the control variable (u_i). The other way, which is the main focus in this thesis, is to use velocity or change in velocity as the control variable. As presented in chapter 3.2.3, different variables in the problem must be discretized in order to solve the problem using dynamic programming. The discretization of variables however causes an error in the variable representing distance (i.e. s_k).

$$x_k = (s_k, v_k), \tag{5.1}$$

$$x_{k+1} = f(x_k, u_k) \tag{5.2}$$

Considering equation 5.2 and the fact that the control variable (i.e. velocity or change in velocity) is always chosen from the same discritization grid as velocity, it can be concluded that v_{k+1} will always fall on the discretization grid of velocity. This is not case for distance, as it is calculated based on equations of motion presented in chapter 3.2.2. The error in each state is defined as the difference between the calculated value and the closest point on the discretization grid. For a trip of around $3\,\mathrm{km\,h^{-1}}$ and $188\,\mathrm{sec}$, the total error is equal to $1.55\,\mathrm{m}$ and the root mean square error in all stages in horizon is equal to $0.15\,\mathrm{m}$. In this example the time, distance and velocity are divided into 40, 5000 and 40 stages respectively.

Another issue with discretization is the problem with coasting mode. Coasting is a mode in which the driver applies zero tractive effort. Due to the fact that change in velocity is assumed to be the control variable, the proposed algorithm can not select coasting mode directly, instead coasting mode is selected by selecting the corresponding control variable (i.e. velocity). Thus, depending on discretization of variables (i.e. length of discretization steps), the solution from the algorithm presented here may not include coasting mode. On the other hand, since change in velocity is assumed to be the control variable, the results include speed holding mode, which may not be the case for algorithms with notch number or tractive effort as control variable.

The algorithm presented consists of two main sets of calculation: offline and online calculation. Offline calculation (i.e. backward iteration within horizon to find optimum decision at each state, see chapter 3.2.3) is done only once for each set of train and track data. Results from the offline calculation can be used on the train for an online DAS. A simulation study shows that although offline calculation can be an extremely time consuming procedure (can be up to 1 hour depending on problem size), online calculation or the calculation done on trains and during operations is extremely fast (less than 0.002 sec). The results from offline calculation are saved and should be stored on the train or on a server to be used for online calculation. In our study the results of offline calculation are saved in a form of a binary file up to 3 GB in size (depending on the number of stages in the horizon and also discretization of state and control variables). It should be noted that the simulations are done using MATLAB on a consumer laptop PC (Intel Core i-5 CPU @ 1.60 GHz and 8GB RAM).

As mentioned in chapter 2, previously presented approaches in the literature use notch number or throttle level as control variable. This approach can also be applied to trains with continuous tractive effort. Paper B discusses the application using tractive effort as control variable for the problem of speed profile optimization of EMUs with continuous tractive effort. The results show that aside from the error in the distance variable, there is also an error in the velocity variable. This is due to the fact that both s_{k+1} and v_{k+1} are calculated based on the control variable (i.e. tractive effort) and it is most likely that s_{k+1} and v_{k+1} do not fall on the discretization grid, and hence they both have to be rounded to the closest point on the grid. Both approaches are tested for speed profile optimization of an EMU with a gliding handle for controlling tractive effort on two $2\,\mathrm{km}$ experimental tracks with different track profiles (i.e. different local speed limits and different slopes). For the sake of comparison, the same number of discretization steps is used for each state variable and horizon in both approaches. Moreover, both approaches have the same number of control variables. In the approach with velocity as the control variable, there are 120 steps for velocity and in the approach with tractive effort as control variable, there are also 120 steps for the tractive effort. This should ensure that the number of calculations done in backward iteration is the same in both approaches; as a result, the time needed for offline calculation will be almost the same in both of the approaches. The results show almost the same root mean square error on distance for both approaches (around $2\,\mathrm{m}$). However, there is also a root mean square error of around $0.3\,\mathrm{km\,h^{-1}}$ on velocity in the approach with tractive effort as the control variable.

5.2 Speed Profile Optimization and Energy Optimal Operation of Battery Driven EMUs

Energy storage devices have been used in the railway industry for decades in the form of stationary and on-board energy storage devices. Stationary energy storage devices are installed at certain points on the track, while on-board storage devices are installed on trains. The main purpose of using storage devices is to increase efficiency of regenerative brake systems. Although energy storage devices have been used in railway section before, EMU's with batteries as the sole energy source have been introduced recently - there have been some battery driven locomotives and trains in the past but the concept of battery driven multiple units is more recent. There are currently two modern battery driven EMUs tested in market. One is developed by East Japan Railway and is in service, and the other one is developed and tested by Bombardier Transportation. Both battery driven EMUs are hybrid battery/catenary EMUs that can be used both under overhead lines and on non-electrified routes.

Paper D deals with speed profile optimization of battery driven EMUs. As presented before in chapter 3.2.4, dynamic programming is applied to this problem with the introduction of state of charge or battery level as the new state variable. As in the problem with normal EMUs, there is an error in the distance variable. Furthermore, there is also an error in battery level (b_i). This is due to the fact that both the distance variable and the battery level variable are calculated based on equations of motion and should be rounded to the closest point on the discretization grid. Simulation results of application of dynamic programming on speed profile optimization of a battery driven EMU running on a track section in the UK (see figures 5.1 and 5.2, results from paper D), shows a root mean square error of $5.42\,\mathrm{m}$ and $0.02\,\mathrm{kWh}$ in distance and battery level respectively. The average distance traveled in one time step is equal to $111.78\,\mathrm{m}$ and the average energy consumption during one time step is equal to $0.78\,\mathrm{kWh}$.

Experiments with different line sections imply that calculation time of backward iteration can be up to 10 hours, but the forward simulation which is to be done on the train still takes less than a second (in the order of milliseconds). The size of the solution of the backward iteration can be up to $10\,\mathrm{GB}$.

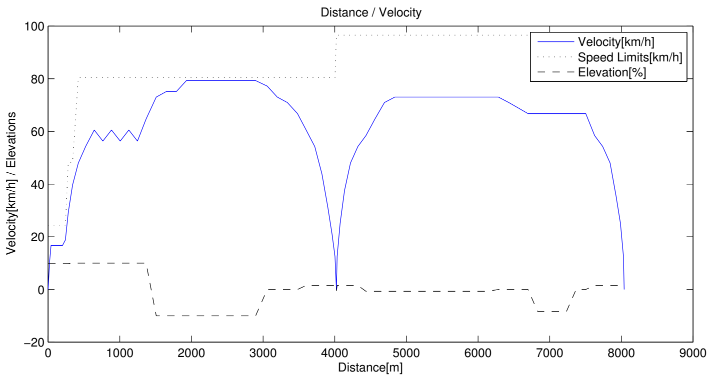


Figure 5.1: Optimum speed profile of a battery driven EMU (Paper D)

The line section used for the simulation experiment with battery driven EMU is an electrified line section in which the real prototype battery driven

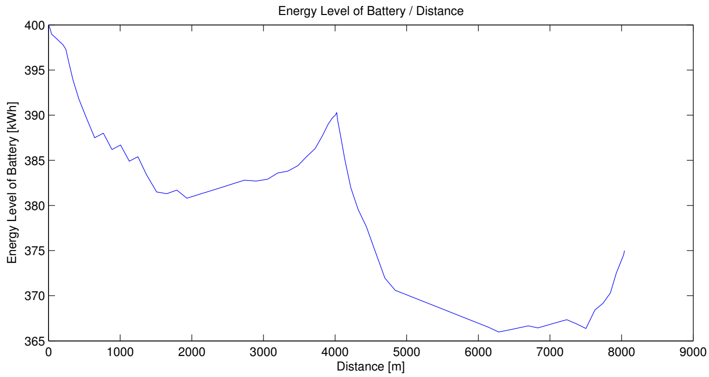


Figure 5.2: Optimum energy profile of a battery driven EMU (Paper D)

EMU was tested. A study on NO_x and CO_2 emissions of a typical diesel multiple unit used in the UK shows that in the case of the battery driven EMU on the same line section, the NO_x and CO_2 emissions are reduced by more than 7 and 27 times respectively. The emission calculations exclude emissions created by the power generation.

5.3 Thesis Contribution

Research questions are answered in this section. The answers are in the form of detailed conclusion drawn from the results presented in sections 5.1 and 5.2, and the literature review presented in chapter 2.

1. **Research Question 1:** *What is the status of application of energy storage devices in trains and what are the existing approaches for speed profile optimization of electric trains and battery driven electric trains?*

   Many approaches are presented for speed profile optimization of electric trains. In general they can be divided into three categories of single train operation, multiple train operation and operation with an energy storage devices.

   Compared with multiple train operation which is a relatively new problem, the problem for single train operation has been studied for several decades, including operation with a secondary energy source other than overhead lines; i.e. an energy storage device. In contrast, the problem for EMUs with an energy storage device as the sole energy source has not been studied much. This is mainly because of the concept of a battery driven electric trains has been introduced relatively recently. Energy storage devices have been used in the railway industry for a long time in the form of stationary (batteries, supercapacitors and flywheels) and on-board (mostly supercapacitors) energy storage devices. In contrast to energy storage devices as secondary energy source, to the best of our knowledge there are only two battery driven passenger EMUs available, both using Li-ion batteries. Consequently, there are no DAS systems available for battery driven EMUs.

2. **Research Question 2:** *How efficient is dynamic programming when used for designing a DAS for EMU's with continuous tractive effort?*

   Discrete dynamic programming is used in this thesis to design a DAS for EMUs and battery driven EMUs. It is assumed that the train modeled in this thesis can be controlled by applying an infinite number of values for tractive effort (i.e. continuous tractive effort), unlike the trains with a limited number of levels on a notched throttle controller(discrete tractive effort). Two approaches are studied when using dynamic programming for the problem with normal EMUs: using velocity as control variable and using tractive effort as control variable. The results show that for the EMUs with continuous values for tractive effort, the approach with velocity as control variable works better as it has a higher accuracy. This is due to the fact that in the approach with tractive effort as control variable, there's an error on two state variables (both distance and velocity). However in the approach with velocity as the control variable, there's an error on only one state variable (i.e. velocity). For the trains with notch system, it is more appropriate to use the tractive effort or throttle level as the control variable. This is because when using velocity as the control variable, there is another error in calculating the tractive effort. The error in the problem with normal EMUs is on calculation of the distance traveled. In a simulation, the total error is about $1.51\,\mathrm{m}$, which is relatively small, considering the train length ($20\,\mathrm{m}$) and trip length ($3\,\mathrm{km}$).

   Both approaches can be used for an online DAS as they are both able to find the optimum decision on-board the train in less than a second (around $0.002\,\mathrm{sec}$). Moreover, each trip/train combination needs an initial solution obtained by offline calculation. The offline calculation can take a long time but this is not an issue as it only needs to be done once for each combination of trip and train configuration. The solution from the offline calculation should be mounted on the train to be used in DAS. The size of such a solution can be up to $3\,\mathrm{GB}$ which is small enough to be mounted on a train computer. Considering the calculation time needed on the train and the error, it can be concluded that discrete dynamic programming with velocity as control variable can be used for speed profile optimization and development of an online DAS for EMUs with continuous tractive effort. However, in case of EMUs with discrete levels on the throttle controller, the approach with tractive effort as control variable performs better.

3. **Research Question 3:** *How efficient is dynamic programming when used for designing a DAS for battery driven EMU's with continuous tractive effort?*

   Dynamic programming with velocity as the control variable is also applied for speed profile optimization of battery driven EMUs. In this case, aside from the error on distance variable, there is also an error on battery level variable. Simulation results show that root mean square error on battery level variable for a certain experiment is equal to $0.02\,\mathrm{kWh}$, which is equal to around 2.6% of the average energy consumption (charge and discharge) in each time step. The time needed for offline calculation is increased substantially in the problem with battery driven EMUs. Nonetheless, it is still manageable as the offline calculation only needs to be done once for each combination of trip and train configuration. Besides, the time needed on the train to find the optimum decision and the speed profile for the rest of the trip is still around a few milliseconds. Same as the problem with the normal EMUs, the results from offline calculations should be stored on the train to be used as an online DAS. The size of the file containing the results of offline calculations is also increased for the problem with battery driven EMUs, to up to $10\,\mathrm{GB}$, which is still small enough to be mounted on a modern train computer. Considering the calculation time needed on the train and the error, it can be concluded that discrete dynamic programming with velocity as control variable can be used for speed profile optimization and development of an online DAS for battery driven EMUs with continuous tractive effort.

Chapter 6

Conclusion

Dynamic programming is used in this research project for speed profile optimization of EMUs and battery driven EMUs with continuous tractive effort. The first two papers (papers A and B) presented in this thesis are focused on normal electric multiple units. Paper A solves the problem for normal EMUs using dynamic programming and velocity as the control variable. The approaches is subsequently compared to the common application of DP in the literature, which proposes the use of tractive effort as the control variable (paper B). The same train model in the same condition is used in both approaches to enable a fair understanding of the differences between the two approaches.

The last two papers (papers C and D) are focused on battery driven electric multiple units. Paper C studies the status of current battery driven trains in the market and their battery types, while paper D discusses the importance of optimal operation of battery driven trains. Paper D focuses mainly on solving the problem of speed profile optimization of battery driven electric trains with continuous tractive effort using discrete dynamic programming. It should be noted that the same basic train model is used for both normal EMU and battery driven EMU. However, it is developed throughout the research and during the publications. The last model presented in paper D is the most complete model.

In conclusion, when solving the problem with dynamic programming, the selection of velocity as the control variable increases the accuracy of results in comparison to the same approach with the tractive effort as the control variable. Dynamic programming is suitable for the development of an online DAS as the time needed on the train to find the best decision is in the order of milliseconds. In addition, the errors caused by discretization of variables are relatively small considering the train length, trips' distances and size of the batteries. However, there is still a need for more improvement in order to use the algorithm for an online DAS.

Chapter 7

Future Work

The future work can be divided into three categories which are as follows:

- Further Development in Train Model

  The main concern about the current train model is energy loss in different components. Currently (presented in paper D) it is assumed that energy efficiency of the whole propulsion system in the modeled EMU is constant. In reality however, the efficiency and more precisely, energy loss varies at different velocities and tractive efforts. Adding a dynamic energy loss instead of a constant coefficient will add to the accuracy of the model.

  Furthermore, it is assumed that voltage in the DC link is constant, which is not the case in reality, especially in the battery driven EMU. DC link voltage (as can be see in figure 3.3) is the same as voltage of batteries. Experience from test runs of battery driven trains shows that battery voltage drops with decrease in state of charge, potentially affecting power calculations (see equations 3.4 and 3.5). There are no models currently of the pattern of voltage drop in relation to decrease in state of charge for our specific case.

  Additionally, there is a need for sensitivity analysis of the current results.

- Validation

  There's a need for validation of the method against real experimental data. The validation should be done both for energy calculations as well as minimization of energy consumption.

- Application on a Real EMU

  The final aim of this project is to create a driver advisory system. The plan is to have the solution presented here in a form of an application for smartphones and tablets and to test the results on a real train. A major challenge in testing the results on a real train is to study drivers' behavior and to provide suitable instructions that take the findings into account.

- Improving Performance of Dynamic Programming

  There is still room for improvement in the use of discrete dynamic programming. Offline calculation time can still be reduced and accuracy can be increased. One of the possibilities is to work with parallel computing.

- Other Approaches

  Other optimization techniques aside from dynamic programming will also be tested. An ongoing work in this field is using a dynamic optimization package in OpenModelica and comparing the results with the current results.

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