SENSITIVITY ANALYSIS AND OPTIMIZATION OF TRACTIVE ENERGY FOR RAILWAY ELECTRIC TRACTION SYSTEM

DISSERTATION/THESIS

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF

MASTER OF TECHNOLOGY
IN
POWER SYSTEM

Submitted by:

Saurabh Gupta

Roll No. 2K14/PSY/16

Under the supervision of

Dr. Priya Mahajan

DEPARTMENT OF ELECTRICAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

2016

DEPARTMENT OF ELECTRICAL ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CERTIFICATE

I, Saurabh Gupta, Roll No. 2K14/PSY/16 student of M. Tech. (Power System), hereby declare that the dissertation/project titled "Sensitivity Analysis And Optimization Of Tractive Energy For Railway Electric Traction System" under the supervision of Dr. Priya Mahajan of Electrical Engineering Department, Delhi Technological University in partial fulfillment of the requirement for the award of the degree of Master of Technology has not been submitted elsewhere for the award of any Degree.

Place: Delhi **SAURABH GUPTA**
Date: 16.06.2016

Dr. Priya Mahajan
Asst. Professor
EED, DTU

ACKNOWLEDGEMENT

I take this opportunity to express my sincere gratitude to all those who have been instrumental in the successful completion of this dissertation.

Dr. Priya Mahajan, Assistant Professor, Dept. Of Electrical Engineering, Delhi Technological University, my project guide, has guided me for the successful completion of this dissertation. It is worth mentioning that she always provided the necessary guidance and support. I sincerely thank her for her wholehearted guidance.

I would like to express my sincere thanks to **Dr. Rachana Garg**, Associate Professor, Electrical Engineering Department, Delhi Technological University for her help and guidance.

I am grateful for the help and cooperation of **Prof. Madhusudan Singh**, Head of the Department of Electrical Engineering, Delhi Technological University, for providing the necessary lab facilities and cooperation. And I wish to thank all faculty members whoever helped to finish my project in all aspects.

I would also like to thank my beloved parents, who always give me strong inspirations, moral supports, and helpful suggestions. Without them, my study career would never have begun. It is only because of them, my life has always been full of abundant blessing. To all the named and many unnamed, my sincere thanks. Surely it is Almighty's grace to get things done fruitfully.

Saurabh Gupta

2k14/PSY/16

ABSTRACT

Railway traction system is a common mode of transportation for long distance travel. It enhances the load carrying capacity and is comparatively cheaper than other modes of transport. Earlier, steam and diesel traction systems were common but now a days, they have been replaced by electric traction system. Electric motors are used in railway electric traction system such as electric multiple units and long distance trains. Such a system when operated under high speeds consumes a lot of energy from the supply line. This leads to increase in the cost of travel. As a result, the minimization of energy consumption with faster and better quality of train operation is desired.

In this dissertation, power flow model of modern railway traction system has been presented and tractive energy consumption using speed-time and speed-distance curve has been studied. Tractive energy consumption model has been developed and sensitivity analysis of the same with respect to parameters of interest has been carried out.

Further, various conventional as well as intelligent techniques of optimization have been studied in detail. Optimization of tractive energy is done by various optimization techniques (e.g. Interior Point Method, Pattern Search Method, Genetic Algorithm and Particle Swarm Optimization) and corresponding optimized parameters are obtained.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

GENERAL

Railway electric traction system is the life-line of transportation in any country. It is the most common mode of public transport for long distance travel. In recent times, the main aim of railway traction system is to provide fast service in order to reduce the urban traffic. The reduction of traffic is necessary for countries like India where a large mass uses railway services for travelling. Modern loco's are either fed with diesel power or electric power. Diesel power loco's burn a large amount of fossil fuel (Diesel) and releases harmful green house gases in the atmosphere. Electric traction system is an environment friendly replacement of diesel powered locomotives. With further electrification of tracks, diesel power locomotives are gradually replaced by electric locomotives these days.

Indian Railway (IR) is the one of the largest organization with the highest electricity consumption in India. It consumes about 2.5% of India's total electricity consumption. In the fiscal year (FY) 2013-14, Indian Railways consumed 17.5 billion kilowatt-hours (kWh), of which 14.14 billion (about 83%) for traction usages and 2.46 billion kilowatt-hours (kWh) (17%) in non-traction usages. Non traction usage includes workshop-0.6 billion kWh (25%), station and service building -0.8 billion kWh (35%), pumping- 0.2 billion kWh (10%) and domestic – 0.7 billion kWh (30%).

Above data clearly shows that Indian railway requires a huge amount of power for traction as well as non traction purposes. Also, as transportation sector is growing very rapidly in India and with railway as a better source of transport, requirement of power will also grow very rapidly in the future.

1.2 RAILWAY ELECTRIC TRACTION SYSTEM

The railway traction substation receives the power from the grid and feeds to the overhead lines known as catenary at suitable points. A pantograph mounted on the roof of the train collects the electric power from the overhead catenary system. This power is then fed to the primary of a single phase locomotive transformer which has three secondary windings. Two of the three windings are fed to the traction drive (tractive energy) and third winding is used to feed the auxiliaries in the locomotives (non-tractive energy). The modern traction drive system comprises of locomotive transformer, converter/ inverter box and traction motor. Fig 1.1 shows the power flow model of modern electric traction system.

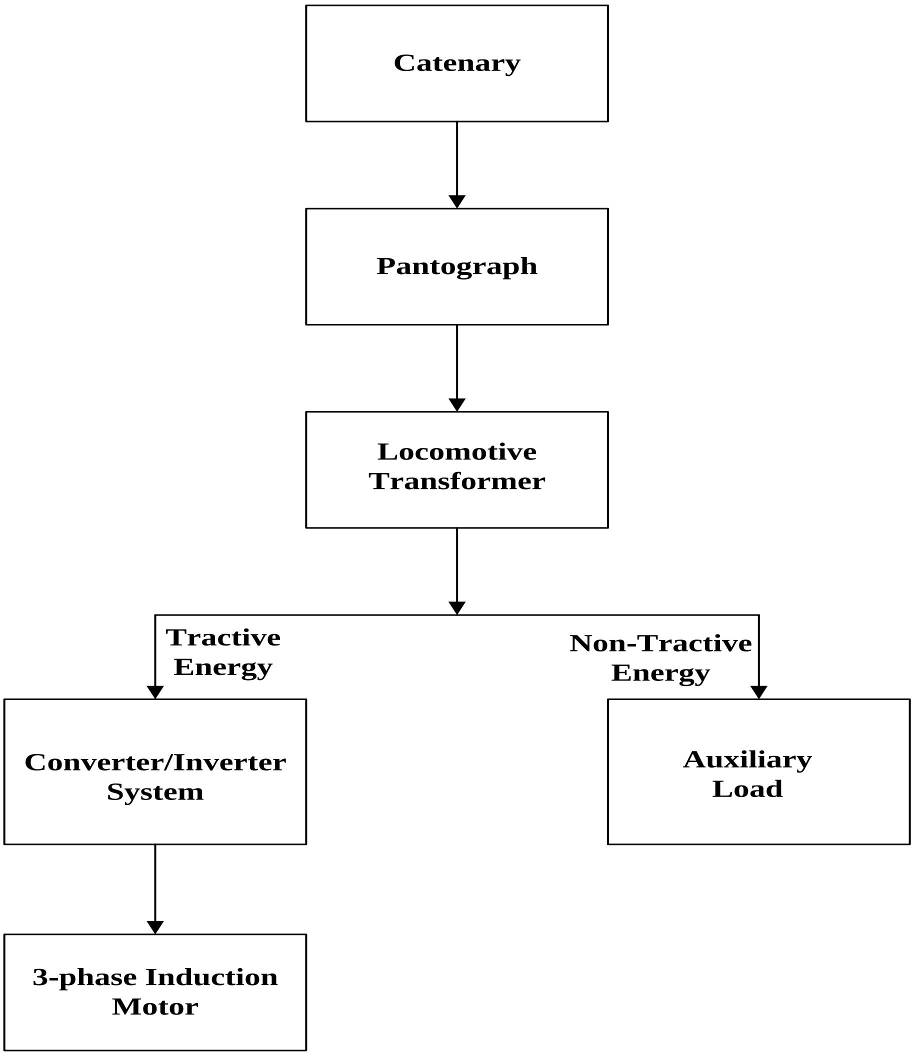

Fig 1.1 Power flow model of modern railway traction system

1.3 MOTIVATION

Railway traction system has become the most common mode of transportation due to the lesser cost of travel and journey time as compared to many of the other modes of travel (e.g. roadways). In India, where cost of travel is a very important factor, importance is given to railways by common people as compared to other modes of transportation. The modern high speed electric drives aims to reduce the journey time. But it will lead to increase in energy consumption in railway traction system due to high accelerations and corresponding high currents which may increase the travelling cost. So, optimization of energy consumption has become a challenge in front of railways because it will lead to decrease in cost of travel without substantially affecting the running time.

In this work, the main focus is kept on the study of tractive energy consumption. Tractive energy consumption model has been developed and sensitivity analysis of tractive energy consumption has been carried out to study the effect of various parameters on the same. Further, various conventional as well as intelligent methods are applied to optimize the tractive energy and a detailed comparison of results obtained has been done.

1.4 PROBLEM FORMULATION

Based on the motivation and utility of the problem, the following objectives have been targeted in this thesis:

i) Study of exact and approximate speed-time curve of train movement, development of tractive energy consumption model based upon approximate speed-time curve and sensitivity analysis of the same.

ii) Study of exact and approximate speed-distance curve of train movement, development of tractive energy consumption model based upon approximate speed-distance curve.

iii) Study of various conventional as well as intelligent methods for optimization and application of these methods on the tractive energy consumption model developed from speed-time as well as speed-distance curve.

iv) Comparison of the results obtained from conventional as well as intelligent optimization methods.

1.5 DISSECTION OF THESIS

The whole work is divided into 7 chapters.

Chapter 1 presents the basic introduction of railway electric traction system, power flow in railway traction system and objective of the thesis.

Chapter 2 contains the literature review of energy consumption in railway traction system, sensitivity analysis and various conventional as well as intelligent optimization methods.

Chapter 3 explains the exact as well as approximate speed-time curves of train movement. Here, tractive energy consumption model for fixed gradient has been formulated using approximate speed-time curve. Further, sensitivity analysis of the tractive energy consumption has been carried out and various graphs of energy consumption have been plotted with respect to parameters of interest.

Chapter 4 explains the exact as well as approximate speed-distance curves. Based upon the approximate speed-distance curve, tractive energy consumption model has been developed for two cases:

i) Variable gradient, constant acceleration

ii) Variable gradient, variable acceleration

Chapter 5 explains the two conventional methods for optimization; Interior point method and Pattern search method. Tractive energy consumption models developed in chapter 3 and 4 have been optimized using these two conventional optimization methods and optimized parameters are obtained.

Chapter 6 explains the two intelligent methods for optimization; Genetic Algorithm and Particle Swarm optimization. Tractive energy consumption models developed in chapter 3 and 4 has been optimized using these two intelligent optimization methods and optimized parameters are obtained.

Chapter 7 gives the comparison of results obtained from conventional as well as intelligent optimization methods.

Chapter 8 gives the conclusion and future scope of work.

1.6 CONCLUSION

In this chapter, a brief introduction and basic power flow model of railway electric traction system has been presented. Also, the motivation of the work and objective of the thesis has been presented. Further, the overview of each chapter is given.

CHAPTER 2
LITERATURE REVIEW

GENERAL

Railway electric traction system is the most common mode of transportation in most of the countries. It is the advanced version of steam and diesel traction systems. Further advancement in electric traction system resulted in the use of regenerative power and increase in system efficiency. The modern electric locomotives are the results of this advancement. These locomotives use 3 phase AC supply where voltage and frequency can be efficiently varied which results in high speed railway operations.

Though, railway electric traction system is a very wide research area, the brief literature review has been carried out without being exhaustive. This literature review covers the topic in this research work as mentioned below:

1) Energy consumption and power flow in railway electric traction system

2) Effect of various parameters on energy consumption model using sensitivity analysis

3) Various conventional as well as intelligent optimization methods and their application on energy consumption.

2.2 RAILWAY ELECTRIC TRACTION SYSTEM

The knowledge of railway and steam engines has been around since the sixteenth century. Wagon roads for English coalmines using heavy planks were first designed and built in 1633. Mathew Murray of Leeds in England invented a steam locomotive that could run on timber rails in 1804 and this was probably the first railway engine. Although railway and locomotive technologies were continually developed, the first known electric locomotive was built in 1837 by chemist Robert Davidson of Aberdeen [1]. This locomotive used galvanic cells as the source of power. Werner von Siemens [2] presented the first electric passenger train in 1879 at Berlin. DC series motor was used in the locomotive. The electricity was supplied through a third insulated rail between the tracks. The operating voltage was 150V DC. This train was having three coaches in addition to locomotive. The first electric tram line in the world was also opened in Germany in 1881. Electric trolleys came into picture in US in 1888 [3]. All the above mentioned system used DC as the source of power. With further development in the traction system, AC came into picture due to the problems associated with DC motors.

M.C. Duffy in [4] presented the detailed study of three phase motor in railway traction system. The advantages of 3 phase AC system over the single phase in terms of losses are presented. Further, the detailed history of AC supply in traction system has been given. Utility power grid and traction power supply system was developed by J. Wang et al [5]. The extent of interaction between these two systems was discussed and power quality improvement methods have been studied based on the harmonic levels and voltage imbalance.

M. Chymera [6] gave the overview of electric traction system in common use. Traction supply system and traction equipments were studied and railway system performance model has been developed. The simplified model of electric railway power supply substation for 3 phase power flow studies has been developed by T. H. Chen et al [7]. This model became the basis for the study of large unbalanced traction load impact on power supply systems. Various transformer connection schemes like scott, V, Le Blanc etc have been studied. Power losses in DC traction system have been studied by D. Gonzalez [8]. Various ways of reducing the power losses in DC system has been presented and voltage control of traction substations has been studied. C. R. Akli et al [9] studied the design of hybrid locomotive which takes into account the energy management strategy based on frequency approach. Study of energy and typical operating frequencies are the main focus of the work. System performance and cost management is also studied. General study of electric locomotive built for service on British Railways has been done by W.J.A. Sykes [10]. Various methods of speed control of DC motors employed in their system have been studied and their impact on energy consumption has been discussed.

Power electronics has it’s own significance in modern railway traction system. The modern microprocessor based drive system is used in the locomotives. The effect of power electronics components on main drives, supply system and auxiliaries has been studied by H. Stemmler [11]. Various modes of operation of the electric traction system using power electronics components have been studied. E. Ohno et al [12] studied the effect of the DC chopper drive using thyristors as switches and various advantages have been listed. Chopper circuitry and it’s application in DC motor speed control has been shown and efficiency improvement due to the above said control has been shown. Z.S. Mouneimne et al [13] gave the simulation techniques for design of traction system. DC electrical terminal characteristics have been presented based upon the inverter controlled asynchronous drives. Further, modification required to use the same model in case of asynchronous AC drives is given.

M.M. Bakran et al [14] presented the detailed comparison of different solutions for multisystem converters. Further, Multisystem locomotive's advantages has been shown. A multi-purpose balanced transformer has been studied by Z. Zhang et al [15] for electric railway application. The various functions of the proposed transformer has been shown and operating principle of the same has been discussed. Further, the harmonic filter design has been studied and simulation results are shown. R. W. Schreywe et al [16] studied the various objectives of modern traction system and the improvement required in the system has been presented. R. Y. Faddoul et al [17] presented the study of auxiliary power supplies for traction system and auxiliary inverters using GTO as controlled switched has been presented. The advantages of Static auxiliary supply systems have also been studied.

There are studies related to regenerative energy also. C. H. Bae et al [18] presented the model for calculation of regenerative energy in a 1500V DC electric traction system and estimated the cost reduction in energy consumption due to the regenerative energy. Electric braking is also studied by F. Whyman [19]. Both regenerative and rheostatic braking for electric traction system has been taken into account and advantages of regenerative braking are presented. E. Agenjos [20] studied the diesel-electric system and applied the resistive braking on the system. Further, regenerative braking has been applied and it has been observed that there is improvement by 15-20% with the help of regenerative braking.

Regenerative braking system for DC traction was analysed by J.M.W. Whiting [21]. A DC series motor was taken into account and field weakening scheme has been applied. It has been observed that regenerative energy can be fed back without much increase in the system cost. X.Chen [22] considered a braking energy recovery system based on super-capacitor. Using the resistive braking and adding a super capacitor resulted in very efficient braking method very similar to regenerative braking. A bi-directional DC-DC converter has been used for charging and discharging of the capacitor. Electrical and mechanical Braking are combinely studied in [23] by T. Koseki et al. Proper instants of braking are defined and various observations have been made.

Taipie Rapid Transit System (TRTS) is considered in [24] by K.H. Tseng et al. Power variations between non-regenerative mode and regenerative mode has been studied for Electric Multiple Units. Further, optimal usage of regenerative power has been ensured. J. Lee et al [25] studied the electric brake system in detail and regenerative braking is focused more. Further, various problems associated with regenerative braking are noticed and remedies of these problems are also provided.

2.3 SENSITIVITY ANALYSIS

Sensitivity analysis is an important criterion for studying the effect of parameter variation on the system. Sensitivity analysis has been carried out by various authors in their studies and various observations have been made. Sensitivity analysis of an electro-mechanical system has been carried out by Q. Wang et al [26] and effect of the variation of both mechanical as well as electrical parameters has been considered. Q. G. Hua [27] has presented a power transformer life cycle cost model and comprehensive as well as conventional sensitivity analysis has been presented. Further, results of these two methods are compared.

L. Lai [28] carried out the sensitivity analysis on hybrid electric vehicles and results obtained from sensitivity analysis have been used for the designing of hybrid electric vehicles. Sensitivity analysis has also been carried out in railway electric traction system. J. Mao [29] studied the methods of characteristics and a new simulation model has been derived. Further, sensitivity analysis of the derived model has been carried out.

P. Mahajan [30] et al derived the series impedance and shunt admittance matrices of railway electric traction system and sensitivity functions are developed. These matrices govern the attenuation and velocity of the signal. Electric motor cooling models have been studied by K. Bennion [31] and various factors related to electric motor thermal management have been studied. Further, sensitivity study has been carried out with respect to these parameters. S. Gupta et al [32] presented the sensitive model of energy consumption by railway electric locomotive. Sensitivity analysis has been carried out by difference equation as well as differentiation methods and results are validated.

Dynamic stability studies have been done by S. Danielsen et al [33] and various operational as well as damping problems are studied. Further, sensitivity analysis of dynamic stability has been done and results obtained from sensitivity analysis have been validated with simulations. P. Mahajan et al [34] studied the pantograph catenary system model and carried out the sensitivity analysis of pantograph model with respect to parameters of interest. Further, the time and frequency response of close loop pantograph model have been studied. An accurate electric model of earth for electric traction system has been presented by S. Jabbehdari et al [35] and sensitivity analysis has been done to evaluate the robustness of the system. M. Brenna [36] studied a 2×25 kV, 50Hz system and carried out the sensitivity analysis of current distribution between the 2×25 kV system branches. Further, the analysis has been validated with simulation and in-field measurements.

2.4 ENERGY CONSUMPTION IN RAILWAY ELECTRIC TRACTION SYSTEM AND OPTIMIZATION TECHNIQUES

Optimization is the act of obtaining the best result under given circumstances. Optimization is used in almost each and every field of engineering directly or indirectly. Whether it's design, construction or any other engineering field, optimization at used directly or indirectly. There are conventional as well as intelligent methods of optimization. Various authors have done their research in the field of optimization. H. Li et al [37] observed that a random search method with gradient oriented directions can be used to optimize a problem effectively without trapping to a local minimum. It also overcomes the shortcomings of random search method alone.

Z.B. Tang et al [38] considered a global optimum problem and an adaptive partitioned random search (APRS) method was employed to optimize the above mentioned global optimization problem. This APRS method was compared with crude random search (CRS) method and it has been observed that APRS is better than CRS in terms of number of function evaluation. C. Zhu et al [39] described the various steps involved in stochastic simulation optimization and compared it with the other optimization method. An analytical formula was derived to find out the number of candidate solutions in each search step.

Optimization has also been used in the railway traction system.

G. D. Irisarri et al [40] proposed a non-linear interior point optimization method to determine the maximum possible loading capacity of power system. Primal-dual and predictor corrector primal-dual interior point algorithms are proposed and a detailed comparison has also been presented. Reactive power optimization with discrete variables on the basis of an interior point filter algorithm has been done by Z. Fan et al [41]. A discrete model was presented and primal dual interior point algorithm was applied to achieve the desired aim i.e. optimization. Study of computing time and calculation efficiency is also done.

Research is also going on the various intelligent methods of optimization. Ant Colony Optimization (ACO) was proposed by M. Dorigo et al [42]. Applications of ACO are presented and advantages of this algorithm have been notified. A microwave semiconductor device modelling was done by M.K. Vai et al [43]. Genetic Algorithm was proposed by J. F. Frenzel et al [44]. The four step process including evaluation, reproduction, recombination and mutation was described for the first time.

Simulated annealing optimization method has been applied to optimize the parameters of the model and also device parameters were obtained. Y. F. Dong et al [45] studied the short comings of ACO and proposed a new algorithm which was the combination of ACO and

Genetic Algorithm (GA). The combined algorithm provided better results as compared to both GA and ACO. Enhanced GA has been studied by P. Guo et al [46]. Hybrid GA, Interval GA and Hybrid Interval GA are presented and these algorithms are compared with each other.

Particle Swarm Optimization (PSO) was first introduced by J. Kennedy et al [47]. Algorithm was tested for non-linear optimization problems and it’s relation with other intelligent optimization techniques e.g. GA was proposed. Improvements are done in the basic PSO algorithm and an improved version was proposed by X. Hu et al [48]. The optimization problem was solved with the basic and improved version of PSO and results are compared.

Optimization methods are also employed in railway traction system. Optimal driving strategy was proposed by Y.V. Bocharnikov et al [49]. A DC sub-urban railway traction systemhas been considered and GA was applied to calculate the tractive energy consumption corresponding to minimum time and minimum energy consumption. The results obtained from the above two cases have been compared and savings in energy have been calculated.

Train running characteristics have also been analyzed and running models are established based upon these characteristics by Y. Fan et al Cai [50]. Multi-objective particle swarm optimization with inertia weight algorithm is applied for optimization. Reduction in energy cost is studied using energy management model by R. A. Uher [51]. This model is used as a power flow simulation tool.

Y.V. Bocharnikov [52] performed the energy optimization using genetic algorithm. Regenerative energy is also taken into account and energy savings data is presented. Genetic Algorithm has also been applied to numerical simulation and energy consumed and running time is calculated by T. Moritani et al [53]. Energy saving using the optimization method (GA) has been presented.

Some researchers have done energy optimization by experimental techniques rather than using simulation methods [54]-[55]. Acampora et al [54] presented a remote measurement system which describes the best approach for energy reduction. An on-board monitoring system is studied which measures the electrical quantities of train and best trip protocol has been developed based on actual measurements [55].

Iterative algorithms are used in order to calculate the energy consumption dynamically and case studies showing comparison of energy consumption for practical and optimal operation are presented by Z. Tian et al [56]. Y. Song [57] studied the dynamic characteristics of high speed train operation and proposed the dual speed curve optimization strategy for high speed train running operation on the basis of traction calculations. L. Shaofeng et al [58] proposed the distance based train trajectory searching model and single train trajectory optimization is done where main focus is to identify optimal train trajectory of a single train. Three optimization tools viz. genetic algorithm, ant colony optimization and dynamic programming are used to achieve this purpose. S. Hillmansen et al [59] developed the equations governing the basic motion of train and various energy saving methods like regeneration, energy storage etc. are analyzed.

2.5 CONCLUSION

This chapter presents the literature review of the railway electric traction system, sensitivity analysis and optimization methods. Latest advancements and research in the field of railway traction system are enlightened. It helps in enhancing the knowledge of the system and provides guidance in the thesis work.

CHAPTER 3
TRACTIVE ENERGY FROM SPEED-TIME CURVE AND IT'S SENSITIVITY MODEL

GENERAL

Energy consumption in railway traction system mainly comprises tractive and non-tractive energy. Tractive energy is the energy required to propel the train i.e. the energy fed to the traction motors. Non-tractive energy is the energy required to feed the auxiliaries in the locomotive like compressors, air-conditioners etc. Tractive energy can be calculated with the data obtained from speed-time or speed-distance curve. Speed-time curve and speed-distance curves are the plots of speed with respect to time and distance respectively. These curves are the basis for the determination of tractive energy.

A speed-time curve shows the variation of train speed with running time of the train. It describes the speed-profile of the train. In order to make a speed-time curve amenable to calculations, it can be approximated (linearised) into a trapezoidal shape. This trapezoidal speed-time curve gives closer approximation to the actual curve for urban and sub-urban services.

In this chapter, tractive effort for propulsion of train and speed-time curve of train movement has been studied and with the help of approximate speed-time curve, the mathematical model of tractive energy consumption has been formulated. This model defines the approximate equations of tractive energy for fixed gradient. Further, sensitivity analysis of energy consumption with respect to parameters of interest has been carried out.

3.2 TRACTIVE EFFORT FOR PROPULSION OF TRAIN

Tractive effort is the effective force required at the wheels of locomotive to propel the train. It is tangential to the driving wheels and measured in Newtons. Tractive effort is required by the train for acceleration, to overcome the effect of gravity and train resistances resisting the motion of the train.

3.2.1 Tractive effort required due to acceleration

The basic equation of force as per Newton's second law is given by (3.1)

$$\text{Force} = \text{Mass} \times \text{Acceleration} \tag{3.1}$$

Let mass of the train be 'm' tonnes, a = acceleration in m/s^2

Therefore, tractive effort, F_a, in N, for linear acceleration is given by (3.2)

$$F_a = (1000 \times m \times a) \tag{3.2}$$

3.2.2 Tractive effort required due to inclination of track

Tracks are not always horizontal and their gradient (slope) varies with the distance. The gradient can be positive or negative. Fig. 3.1 shows the tractive efforts required due to inclination of track.

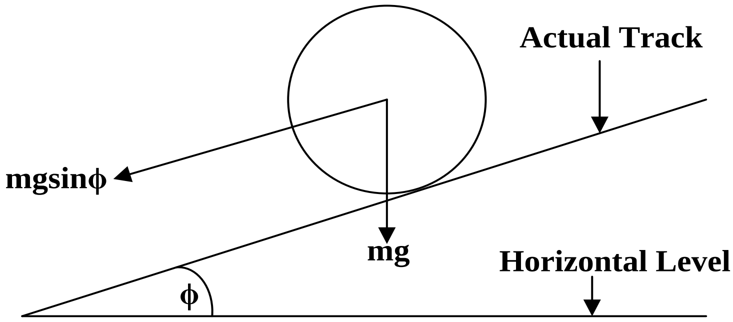

Fig. 3.1 Tractive effort due to inclination of track

Force due to the gradient, F_g, in N, is given by (3.3)

$$F_g = (1000 \times m \times sin\phi \times g) \quad (3.3)$$

where, ϕ = gradient of track with respect to ground and g = acceleration due to gravity

In railway, gradient is expressed as rise in meters in a track distance of 100m and is denoted by percentage gradient G as given by (3.4)

$$\left(sin\phi = \frac{G}{100}\right) \quad (3.4)$$

So, tractive effort due to track inclination on further simplification is given by (3.5)

$$F_g = \left(1000 \times m \times \frac{G}{100} \times g = 98.1mG\right) \quad (3.5)$$

3.2.3 Tractive effort required due to train resistance

Train resistance consists of all the forces resisting the motion of a train when it is running at uniform speed on a straight and level track. Train resistance is due to

(i) The friction at various parts of rolling stock.

(ii) Friction at the track

(iii) Air resistance

General equation for train resistance, r, in N/tonnes, is given by (3.6)

$$r = \left(k_1 + k_2 \times V_m + k_3 \times V_m{}^2\right) \quad (3.6)$$

where, k_1, k_2 and k_3 are Davis constants depending upon the train and the track and r is the specific resistance and V_m = maximum velocity

Tractive effort required to overcome the train resistance, F_r , in N, is given by (3.7)

$$F_r = (m \times r) \quad (3.7)$$

Total tractive effort required to run a train on track is the sum of tractive effort required for linear and angular acceleration, tractive effort due to track inclination and tractive effort to overcome the train resistance and is given by (3.8)

$$F_t = (m \times a \pm 98.1m \times G + m \times r) \quad (3.8)$$

where, positive sign is for motion of the train up the gradient and negative sign is for motion of the train down the gradient.

3.3 TRACTIVE ENERGY CONSUMPTION USING SPEED-TIME CHARACTERISTICS OF LOCOMOTIVE [32]

The movement of trains and their energy consumption can be studied by means of speed-time curve. Speed-time curve shows the speed at different time instants after the start of run. In the upcoming sections, exact and approximated speed-time curve has been studied and equation of energy consumption has been derived using the approximate curve.

A typical speed-time curve of train movement is shown in fig. 3.2.

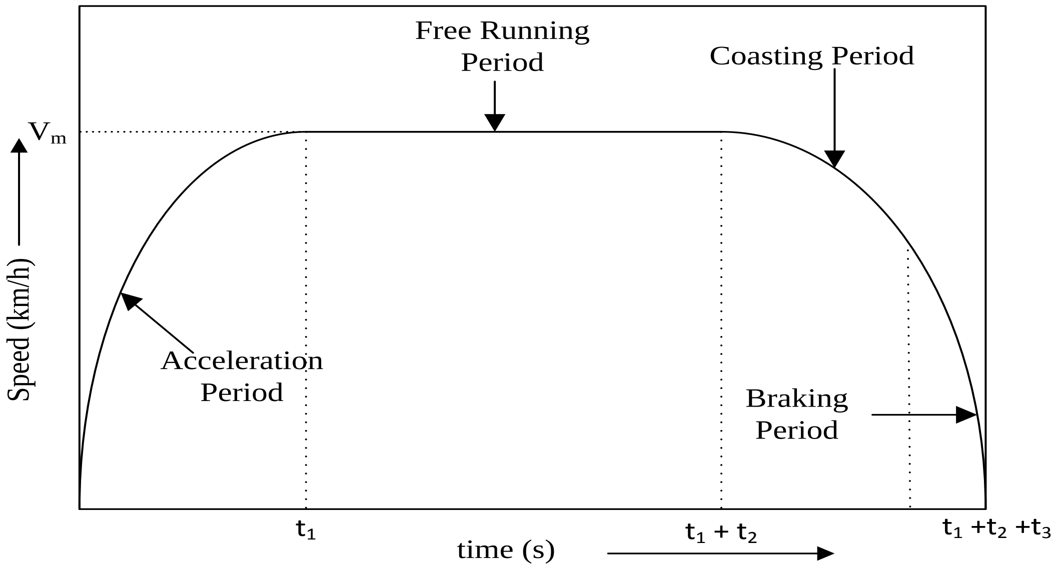

Fig 3.2 A Typical Speed-time curve of train movement

Speed time curve mainly consists of

1. Initial acceleration period
2. Constant speed run/Free run period
3. Coasting period
4. Retardation /Braking period

a) Initial acceleration period:-It gives the information about starting acceleration which is to be provided to run the train. At the end of this period, train attains maximum speed. Train draws maximum power during this period.

b) Constant speed run/free run period:-During this period the train runs with constant speed and it draws constant power from the supply.

c) Coasting period:-During this period, power supply is cut-off and train runs due to it's own momentum i.e , train runs due to the kinetic energy gained by the wheels and don't draw any power from the supply. As a result it's speed goes on decreasing. The rate of decrease of speed during coasting period is called coasting retardation.

d) Retardation or braking period:-During this period, brakes are applied to bring the train to rest. During this period, the speed decreases rapidly and finally reduces to zero.

In order to study the train performance conveniently, the speed time curve is replaced by approximate simplified speed-time curve. From this simplified curve, the relationships between acceleration, retardation, average speed and distance can be easily worked out. These can have either quadrilateral or trapezoidal shape. An approximate speed-time curve is shown in fig 3.3.

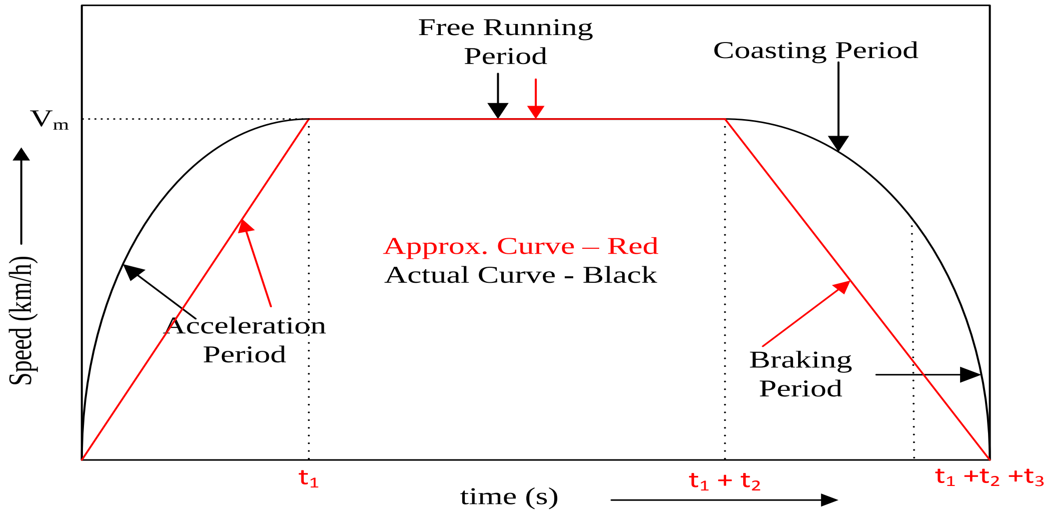

Fig.3.3 An approximated Speed-time curve

In the approximated speed time curve, acceleration is assumed constant till the train attain maximum speed and coasting period is neglected. It is also assumed that train de-accelerates at a constant rate.

3.4 TRACTIVE ENERGY CONSUMPTION FOR FIXED GRADIENT USING SPEED-TIME CURVE

An approximated speed-time curve of the train movement is shown above in fig.3.3. It can be divided into three periods:

(i) constant acceleration period

(ii) constant speed period

(iii) braking period

Energy is consumed during constant acceleration period to run the train from rest to a speed V_m, and is given by (3.9)

$$E_{t1} = [½ \times (F_{t1} \times V_m \times t_1] \quad (3.9)$$

where, F_{t1} is the tractive effort required due to acceleration, gravity and tractive resistance up to time t_1 and is given by (3.10)

$$F_{t1} = ma \pm mg\sin\phi + mr \quad (3.10)$$

During constant run period, the train runs at constant speed. Energy consumed to run the train at the speed V_m is required only to overcome the gradient and resistance to motion is given by (3.11)

$$E_{t2} = (F_{t2} \times V_m \times t_2) \quad (3.11)$$

where, F_{t2} is the tractive effort required from time t_1 to t_2 and is given by (3.12)

$$F_{t2} = \pm mg\sin\phi + mr \quad (3.12)$$

Assuming that the train is not consuming any power during braking period, the net energy input is given by (3.13).

$$E = E_{t1} + E_{t2} \quad (3.13a)$$

$$E = mV_m \left[\left(\frac{a \pm g\sin\emptyset + r}{2} \right) \times t_1 + (\pm g\sin\emptyset + r) \times t_2 \right] \quad (3.13b)$$

Now, this basic equation defined in (3.13) can be used to calculate the tractive energy for positive, negative and zero gradients. Data for calculating the tractive energy consumption for positive, negative and zero gradients is given in Table - 3.1 The corresponding equations are given by (3.14) - (3.16) respectively.

TABLE 3.1 TYPICAL DATA OF A LOCOMOTIVE [32, 57]

Parameter	**Value**
Acceleration time 't_1'	30 sec
Free running period 't_2'	70 sec
Acceleration 'a'	0.56 m/s^2
Mass 'm'	213 tonnes=2.13×10^{5} kg
Gradient 'sinϕ'	2×10^{-3}
k_1	3.73KN=1.9×10^{-2} N/kg
k_2	8.29×10^{-2} KN/m/s = 4.2×10^{-4}N/m/s/kg
k_3	4.3×10^{-3} KN/m/s^2=2.19×10^{-5} N/m/s^2/kg

$$E_p = 10^4 \times V_m[10.65\alpha t_1 + 1.14 t_1 + 2.28 t_2] \quad (3.14)$$

$$E_n = 10^4 \times V_m[10.65\alpha t_1 + 0.72 t_1 + 1.44 t_2] \quad (3.15)$$

$$E_z = 10^4 \times V_m[10.65\alpha t_1 + 0.93 t_1 + 1.86 t_2] \quad (3.16)$$

3.4.1 Variation of tractive energy consumption with respect to parameters of interest

To study the effect of parameters of interest on energy consumed by the locomotive, the graphs of energy with respect to a particular parameter are plotted. While plotting the graph with respect to a particular parameter, other parameters are treated as constant and data to plot these graphs has been taken from Table-3.1. Fig. 3.4 -3.8 shows the variation of energy consumption with respect to mass 'm', acceleration '*a*', acceleration time 't_1', free run period 't_2'and maximum velocity 'V_m'.

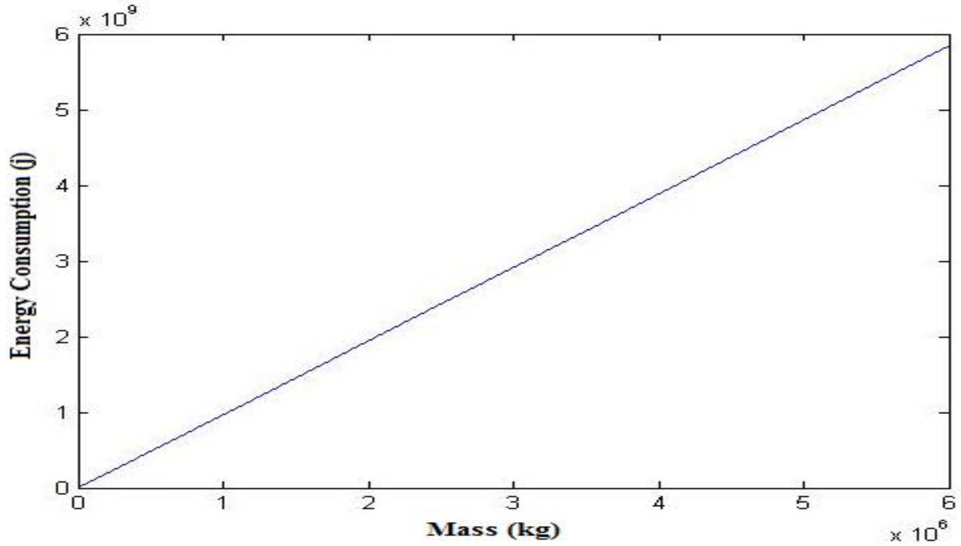

Fig.3.4. Variation of energy consumption with respect to mass 'm'

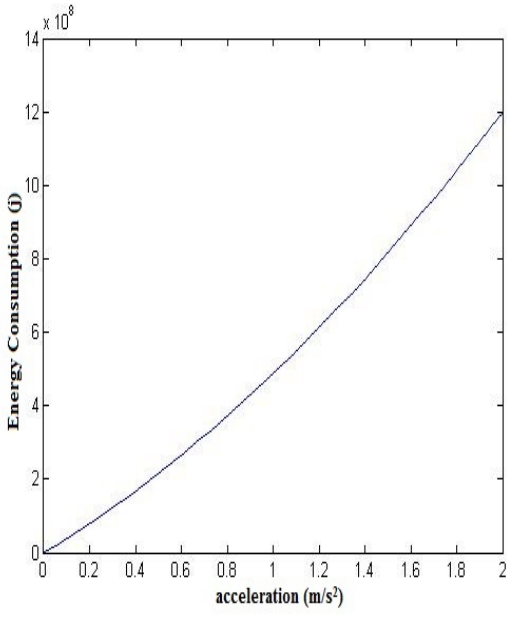

Fig. 3.5. Variation of energy consumption with respect to acceleration '*a*'

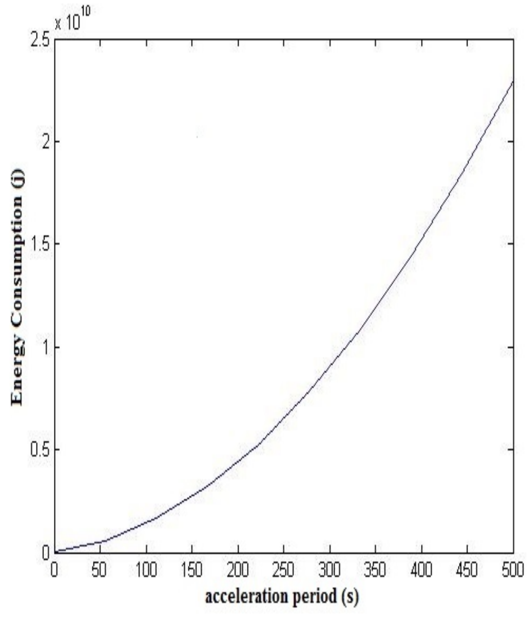

Fig. 3.6 Variation of energy consumption with respect to acceleration period 't_1'

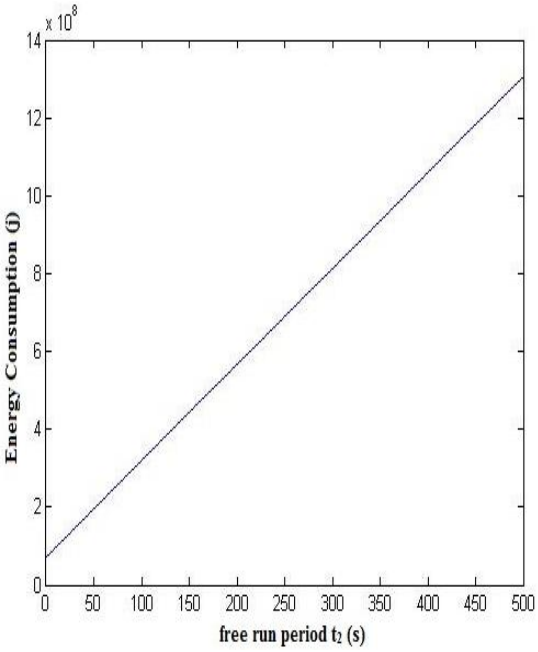

Fig.3.7 Variation of energy consumption with respect to free run period 't_2'

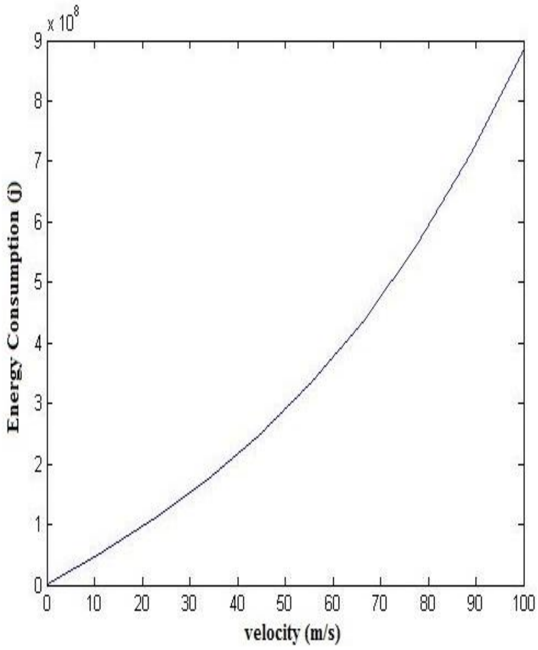

Fig.3.8 Variation of energy consumption with respect to velocity 'V_m'

It has been observed that energy consumption variation is a straight line with respect to mass and free run period 't_2' and a parabola with respect to acceleration time 't_1' and acceleration 'a' respectively.

3.5 SENSITIVITY MODEL OF TRACTIVE ENERGY CONSUMPTION [28-36]

The normalised sensitivity of a quantity 'A' is defined as the percentage change in its output when there is one percent change in one of the input parameters 'B'. Mathematically, it is defined by (3.17)

$$\hat{S}_B^A = \frac{\partial A}{\partial B} \times \frac{B}{A} \tag{3.17}$$

Sensitivity analysis is an important criterion while designing a system. It provides the important information for the designer and system analyst regarding parameter variation and guides to take the corrective action in order to obtain a desired response from the system.

Sensitivity analysis shows how a system changes with variations in its input parameters. The results of a sensitivity analysis can be used to validate a model, to warn of strange or unrealistic model behaviour, to suggest new experiments or guide future data collection efforts, to point out important assumptions of the model, to suggest the accuracy to which the parameters must be calculated, to guide the formulation of the structure of the model, to adjust numerical values for the parameters, and to allocate resources.

The sensitivity analysis tells which parameters are the most important and most likely to affect predictions of the model. Following a sensitivity analysis, values of critical parameter scan can be refined while parameters that have little effect can be simplified or ignored. In this section, sensitivity analysis of energy consumed by railway locomotive is carried out in order to find out the effect of parameters of interest on energy consumed by the locomotive.

3.5.1 Sensitivity analysis using sensitivity functions

Considering the equation of energy as given by (3.13), sensitivity functions with respect to parameters of interest can be developed as given by (3.18) - (3.22).

a) Sensitivity function of energy with respect to mass 'm' is given by (3.18)

$$\hat{S}_m^E = \frac{\partial E}{\partial m} \times \frac{m}{E} \tag{3.18a}$$

$$=1 \tag{3.18b}$$

b) Sensitivity function of energy with respect to acceleration '*a*' is given by (3.19)

$$\hat{S}_a^E = \frac{\partial E}{\partial a} \times \frac{a}{E} \tag{3.19a}$$

$$= \frac{\frac{a \times t_1}{2}}{\frac{(a \pm gsin\emptyset + r)}{2} \times t_1 + (\pm gsin\emptyset + r) \times t_2} \tag{3.19b}$$

c) Sensitivity function of energy with respect to acceleration period 't_1' is given by (3.20)

$$\hat{S}_{t_1}^E = \frac{\partial E}{\partial t_1} \times \frac{t_1}{E} \tag{3.20a}$$

$$= \frac{\frac{(a \pm gsin\emptyset + r)}{2} \times t_1}{\frac{(a \pm gsin\emptyset + r)}{2} \times t_1 + (\pm gsin\emptyset + r) \times t_2} \tag{3.20b}$$

d) Sensitivity function of energy with respect to free running period 't_2' is given by (3.21)

$$\hat{S}_{t_2}^E = \frac{\partial E}{\partial t_2} \times \frac{t_2}{E} \tag{3.21a}$$

$$= \frac{(\pm gsin\emptyset + r) \times t_2}{\frac{(a \pm gsin\emptyset + r)}{2} \times t_1 + (\pm gsin\emptyset + r) \times t_2} \tag{3.21b}$$

e) Sensitivity function of energy with respect to velocity 'V_m' is given by (3.22)

$$\hat{S}_{Vm}^E = \frac{\partial E}{\partial V_m} \times \frac{Vm}{E} \tag{3.22a}$$

$$= \frac{[0.5(a \pm gsin\emptyset + k_1) + V_m k_2 + 1.5V_m^2 k_3]t_1 + [\pm gsin\emptyset + k_1 + 2V_m k_2 + 3k_3 v_m^2]t_2}{\left(\frac{a \pm gsin\emptyset + r}{2}\right) \times t_1 + (\pm gsin\emptyset + r) \times t_2} \qquad (3.22b)$$

The above developed functions can be used to study the effect of these parameters on energy consumed.

3.5.2 Sensitivity analysis using difference equations

Sensitivity analysis can also be carried out using difference equations. Normalised Sensitivity of a quantity 'A' with respect to quantity 'B' using difference equation is defined by (3.23)

$$\hat{S}_B^A = \frac{A_1 - A_2}{A_1} \times 100 \qquad (3.23)$$

where, A_1=Value of quantity A at certain input parameters

A_2= Value of quantity 'A' on decreasing input parameter 'B' by 1 percent keeping other input parameters same.

Difference Equation is a simple method for sensitivity analysis which doesn't involve any derivative and can be used effectively when it is difficult to obtain the derivative of function under study without the loss of accuracy.

Normalised Sensitivity of energy consumption with respect to the parameters of interest is calculated using sensitivity functions (3.18) - (3.22) as well as difference equations method (3.23). The result of Sensitivity analysis using sensitivity function and difference equations are shown in Table - 3.2. Data assumed is given in Table - 3.1. It has been observed that results obtained by both the methods are almost same.

TABLE 3.2 NORMALIZED SENSITIVITY RESULTS

Normalized Sensitivity ($\hat{S}_P^E$) → **Parameter ↓**	**Normalized Sensitivity using Sensitivity functions**		**Normalized Sensitivity using Difference equations**	
	Positive Gradient	**Negative Gradient**	**Positive Gradient**	**Negative Gradient**
Mass 'M'	1	1	1.00	1.00
Acceleration 'a'	0.656	0.886	0.65	0.87
Acceleration period 't_1'	0.716	0.906	0.73	0.89
Free running period 't_2'	0.283	0.1	0.28	0.1
Velocity V_m	0.93	1.1	0.96	1.13

It has been observed that tractive energy is most sensistive with respect to maximum velocity and least sensitive with respect to free running period for positive as well as negative gradient.

3.6 CONCLUSION

In this chapter, tractive effort for propulsion of train has been studied and equation of tractive effort has been derived. Speed-time curve has been studied and mathematical model of tractive energy consumption has been developed using approximated speed-time curve with fixed gradient and variation of energy consumption with respect to various parameters of interest has been plotted Sensitivity analysis of tractive energy consumption has been carried out and it has been observed that energy is most sensitive with respect to maximum velocity.. These studies will guide the designer while designing the parameters of system to minimize the energy consumption and will be helpful in optimizing the energy consumption of the locomotive.

CHAPTER 4
TRACTIVE ENERGY FROM SPEED-DISTANCE CURVE

GENERAL

Energy consumption model has already been derived using speed-time curve for fixed gradient and acceleration. In actual scenario, gradient doesn't remain constant and varies with respect to distance. A speed-time curve is well suited as long as the gradient is assumed constant. To accommodate the effect of variable gradient with respect to distance travelled by the train, speed-distance curve is more suitable. A speed-distance curve shows the variation of train speed with respect to distance travelled by the train. In actual, speed-distance curve is non-linear like a speed-time curve. In order to make it suitable for calculations, speed-distance curve is approximated by linear curves. It can be approximated by trapezoidal as well as quadrilateral curves. A trapezoidal curve provides good approximation and makes the calculations very simple.

In this section, actual and approximate speed-distance curve has been studied and energy consumption model has been derived using the approximate speed-distance curve. Effect of regenerative braking is also taken into account. Initially acceleration and de-accelerations are assumed constant for accelerating and braking period respectively and gradient is varied and energy consumption model has been developed. Further, acceleration and de-accelerations are divided into two parts for acceleration and braking period respectively to make the approximate speed-distance curve closer to actual curve and energy consumption model has been developed. These energy consumption models will further be optimized in the upcoming chapters.

4.2 TRACTIVE ENERGY CONSUMPTION USING SPEED-DISTANCE CHARACTERISTICS OF LOCOMOTIVE

Train movement and energy consumption can be most conveniently studied using speed-distance curve when gradient is variable along a given distance. A speed-distance curve is the plot of speed with respect to distance. Like a speed-time curve, it contains acceleration period, free running period, coasting period and braking period. All these periods are already explained in section 3.4. A typical speed-distance curve is shown in fig 4.1.

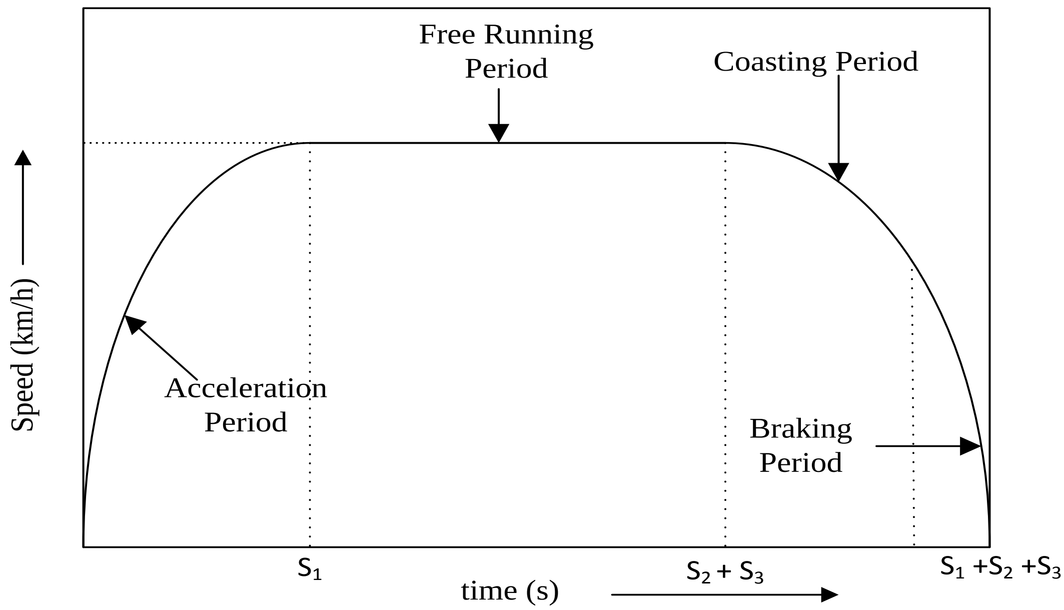

Fig. 4.1 A typical Speed-distance curve

where, S_1 is the distance travelled during acceleration period, S_2 is the distance travelled during free run period and S_3 is the distance travelled during braking period.

In order to study the performance of a service at different schedule speeds, the actual speed distance curve is replaced by simple geometric shaped curve. From this simplified curve, the relationships between acceleration, retardation, average speed and distance can be easily worked out. An approximate speed-distance curve is shown in fig 4.2

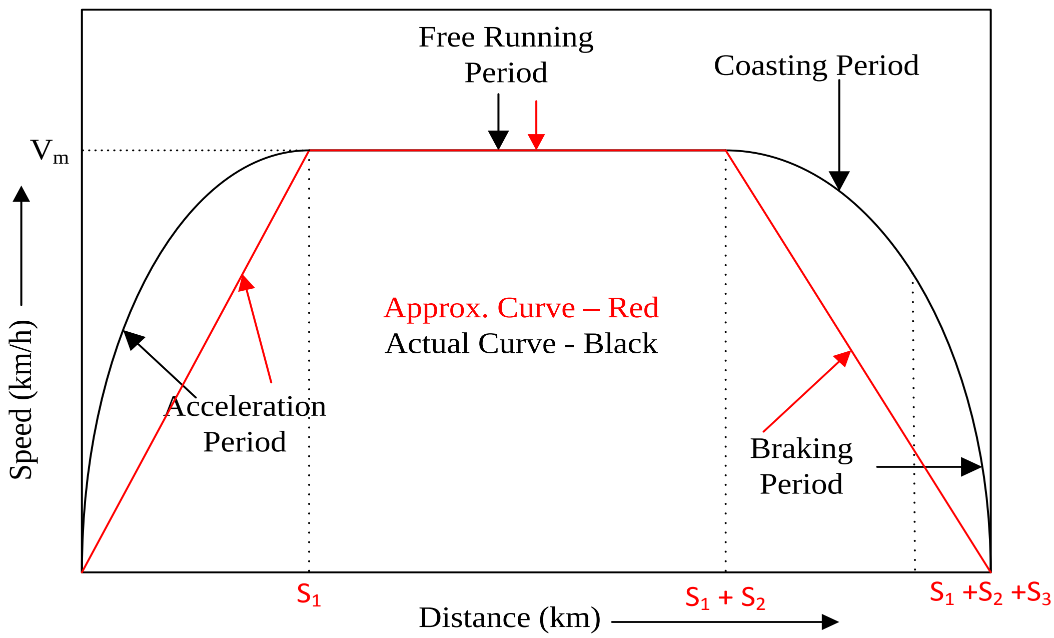

Fig. 4.2 An approximate speed-distance curve

In the approximate speed-time curve, acceleration is assumed linear and coasting period is neglected. Regenerative energy generated during braking period is also taken into account while calculating energy from speed-distance curve.

4.2.1 Tractive energy consumption using simplified speed-distance curve

Energy consumed during acceleration period, E_{s1}, is given by (4.1)

$$E_{s1} = F_{t1} \times S_1 \quad (4.1)$$

where, F_{t1} is the tractive effort for acceleration period and is given by (4.2)

$$F_{t1} = ma \pm mgsin\phi_1 + mr \quad (4.2)$$

Here, a = acceleration, g = acceleration due to gravity, $sin\phi_1$= gradient during acceleration period, r = specific resistance as already defined by (3.6)

Energy consumed during free run period, E_{s2}, is given by (4.3)

$$E_{s2} = F_{t2} \times S_2 \quad (4.3)$$

where, F_{t2} is the tractive effort required during free run period and is given by (4.4)

$$F_{t2} = \pm mgsin\phi_2 + mr \quad (4.4)$$

where, $sin\phi_2$= gradient during free running period

Similarly, Regenerative energy during braking period, E_{s3}, is given by (4.5)

$$E_{s3} = F_{t3} \times S_3 \quad (4.5)$$

Where, F_{t3} is the tractive effort during braking period and is defined by (4.6)

$$F_{t3} = -(m\beta \pm mgsin\phi_3 + mr) \quad (4.6)$$

where, β = de-acceleration, $sin\phi_3$= gradient during braking period

Total energy is the summation of (3.24), (3.25) and (3.26) and is given by (4.7)

$$E = E_{s1} + E_{s2} + E_{s3} \quad (4.7)$$

Equation (4.7) is the basic equation of energy consumption derived from speed-distance curve. Now this basic energy equation is used in formulating the energy consumption model using real-time data. In the equation (4.7), it has been assumed that acceleration and de-acceleration remains constant for acceleration and braking period respectively. These acceleration and de-acceleration will further be divided into two parts and more accurate energy consumption model is formed using real-time data.

4.2.2 Tractive energy consumption for variable gradient and fixed acceleration

Consider the particular section of the route between London Paddington and Briston. It is an 8.53 km long section. Although longer than on some suburban railway lines where between 2 and 6 km is more typical, this section provides sufficient opportunities for energy savings and gives enough variations of speed limit and gradient to demonstrate the applicability of the method to real situations.

This railway section is further divided into 7 sub -sections. Each sub-section has variable gradient and variable maximum speed. As already observed in chapter 3 (3.18), energy consumption is directly proportional to mass. Further, mass of the train is not constant and depends upon the passenger mass and rotary allowance of motors, so variation of mass is also taken into account as per the real time data and is given by Table - 4.1. Specifications for the railway section are given by Table - 4.2

TABLE 4.1 DATA ASSUMED FOR TRAIN [49]

Parameter	**Value**
Rolling stock mass , m_{rs} (tonnes)	162
Rotary allowance of motors	0.06 m_{rs}
Passenger mass	0.15 m_{rs}
Effective mass (m)	m_{rs} (1+0.06+0.15)

TABLE 4.2 SPECIFICATIONS OF LONDON-BRISTON RAILWAY SECTION [49]

Section	1	2	3	4	5	6	7
Length (km)	0-2.09	2.09-2.57	2.57-3.22	3.22-4.5	4.5-6.1	6.1-7.4	7.4-8.53
Gradient (%)	1.124	0	-1.276	-0.757	0	-0.753	0
Speed-Limit (km/h)	90	90	100	100	60	80	80

It can be seen from the above data that gradient and maximum speed are different for each sub-sections. Also, there are positive, negative and zero gradients coming into picture for different sub-sections. So this section considers all the possible cases which happen in real time.

Based on the above data, the speed-distance curve can be plotted as shown in fig.4.3 and using the speed-distance curve, equation of energy consumption (in Joules) can be formulated for all the seven sections and is given by (4.8) - (4.14) respectively.

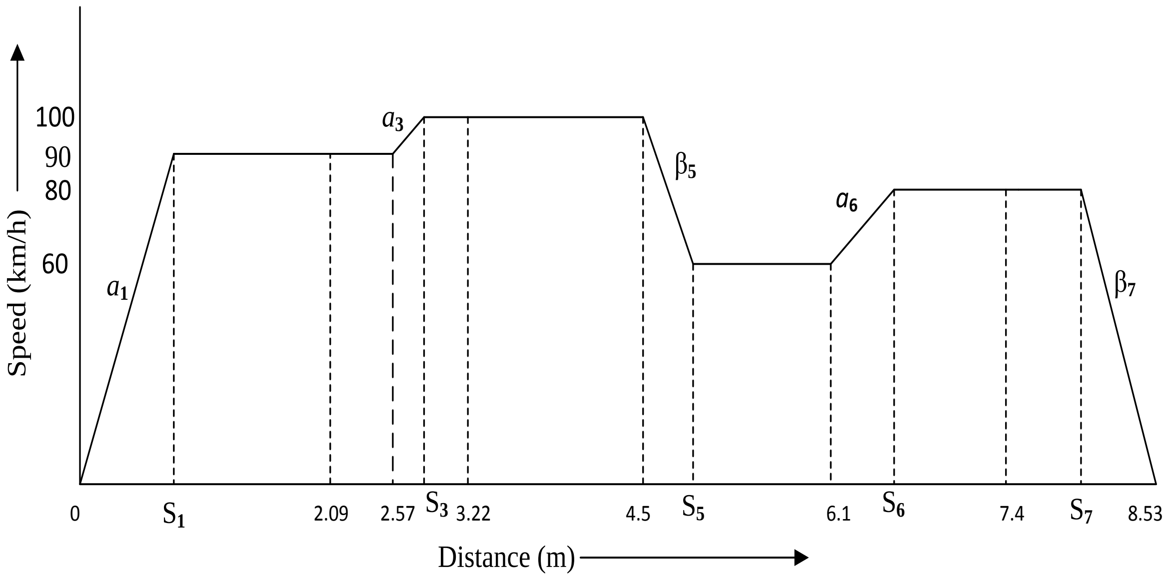

Fig. 4.3 Speed-Distance curve of London-Briston Railway section

$$E_1 = 1.96\times 10^5(\alpha_1 s_1) + 6.28\times 10^7 \tag{4.8}$$

$$E_2 = 4.075 \times 10^6 \tag{4.9}$$

$$E_3 = 1.96\times 10^5 (\alpha_3 s_3) - 9.85\times 10^6 \tag{4.10}$$

$$E_4 = -6.6 \times 10^6 \tag{4.11}$$

$$E_5 = -1.96\times 10^5 \beta_5 s_5 + 3044.528146\times s_5 + 51.47935805 \tag{4.12}$$

$$E_6 = 1.96\times 10^5 \alpha_6 s_6 - 8.8\times 10^6 \tag{4.13}$$

$$E_7 = -1.96\times 10^5 s_7 + 8.6 \times 10^6 \tag{4.14}$$

Total energy is given by (4.15)

$$E = \sum_{i=1}^{7} E_i \tag{4.15}$$

where, a_1, a_3 and a_6 represents the acceleration for sub-sections 1,3 and 6 respectively., β_5 and β_7 represents the de- acceleration for sub-sections 5 and 7 respectively, r_2 *and* r_4 represent the specific resistances for sub-sections 2 and 4 respectively. $s_1, s_2, \ldots s_7$ are the distances travelled by the train as indicated in fig. 4.3. It is assumed that 80% of energy during regenerative braking is fed back to the system.

4.2.3 Tractive energy consumption for variable gradient and variable acceleration

In the previous section, equation of energy consumption has been formulated using speed-distance curve assuming that the acceleration and de-acceleration remains constant throughout the acceleration and de-acceleration period respectively. Now acceleration and de-accelerations are further divided into two sections and equation of energy consumption has been formulated using new speed-distance curve as shown in fig. 4.4.

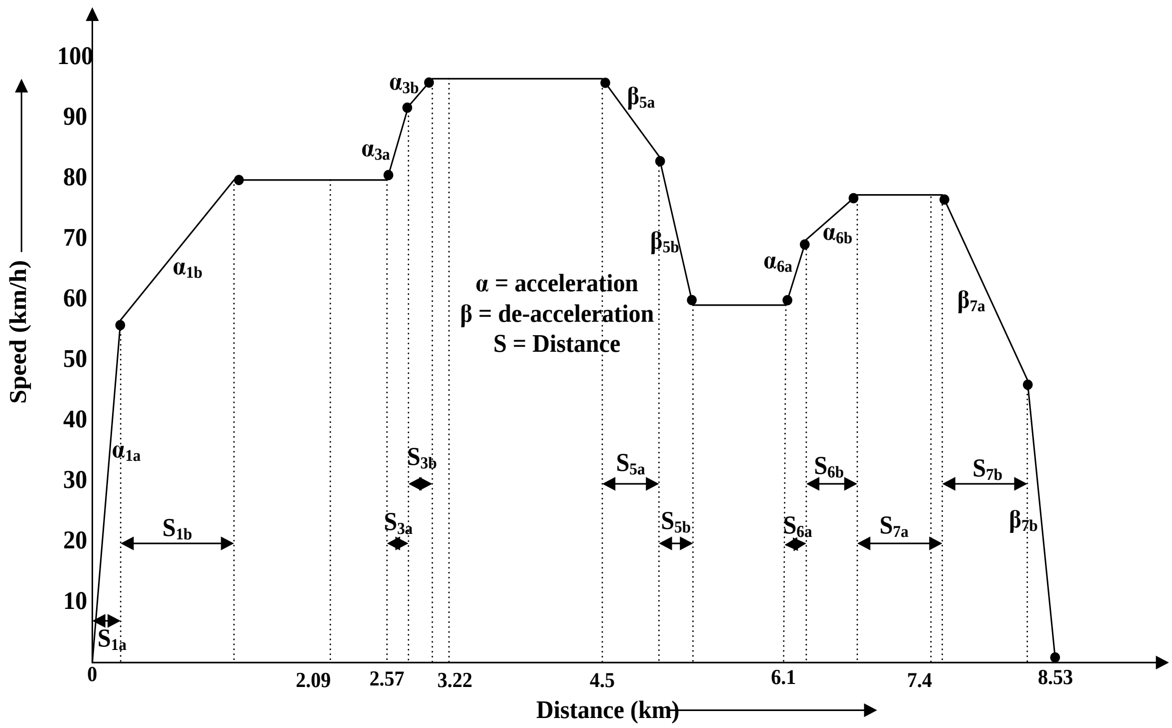

Fig. 4.4 Speed-distance curve of London-Briston Railway section with acceleration divided

Based on the data provided by Table 4.1 and 4.2 and using the speed-distance curve shown in fig. 4.4 equation of energy consumption (in Joules), can be formulated for all the seven sections and is given by (4.16) - (4.22) respectively.

$$E_1 = 1.96\times 10^5\,(\alpha_{1a}s_{1a} + \alpha_{1b}s_{1b}) - 2.14\times10^3\times s_{1a} + 6.27\times10^7 \quad (4.16)$$

$$E_2 = 4.075 \times 10^6 \quad (4.17)$$

$$E_3 = 1.96\times 10^5\,(\alpha_{3a}s_{3a} + \alpha_{3b}s_{3b}) - 3.52\times10^2\times s_{3a} - 1.57\times10^7 \quad (4.18)$$

$$E_4 = -6.6 \times 10^6 \quad (4.19)$$

$$E_5 = -1.96\times 10^5(\beta_{5b}s_{5a} + \beta_{5b}s_{5b}) + 3.03\times10^3\times s_{5a} + 1.86\times10^3\times s_{5b} + 8.07\times10^6 \quad (4.20)$$

$$E_6 = 1.96\times 10^5\ (\alpha_{6a}s_{6a} + \alpha_{6b}s_{6b})\ -4.90\times10^2\times s_{6a}\ -1.49\times10^7 \quad (4.21)$$

$$E_7 = -1.96\times 10^5\ (\beta_{7a}s_{7a} + \beta_{7b}s_{7b})\ -2.10\times10^3\times s_{7b}\ +8.70\times10^6 \quad (4.22)$$

Total energy is given by (4.23)

$$E = \sum_{i=1}^{7} E_i \quad (4.23)$$

4.3 CONCLUSION

In this chapter, speed-distance curve has been studied and tractive energy consumption model has been formulated using approximated speed-distance curve. This model is formulated for two cases:

(i) Gradient is varied and acceleration and de-acceleration are assumed constant for acceleration and de-acceleration periods respectively.

(ii) Gradient as well as acceleration and de-acceleration are varied.

Effect of regenerative braking is also taken into account for both the cases. The tractive energy consumption model developed in these sections will further be optimized in the next chapters.

CHAPTER 5

ENERGY OPTIMIZATION USING CONVENTIONAL OPTIMIZATION METHODS

GENERAL

Optimization is the act of obtaining the best result under given circumstances. There are conventional as well as intelligent methods available for optimization. Every method has some advantages as well as disadvantages. This chapter presents the conventional methods for constrained optimization. There are various conventional methods available which includes random search method, complex method, sequential linear programming method, Rosen's gradient projection method, Interior point method, Pattern search method etc. All these methods are used to solve constrained optimization problems. These methods differ from each other in the way they deal with problems and constraints. Some of these methods may include derivatives also. The energy consumption equations derived earlier are can be optimized under various constraints using these conventional methods. In this work, two conventional methods (Pattern search method and Interior point method) are used to optimize energy consumption. Various constraints presents due to the motion of the train are taken into account.

5.2 INTERIOR POINT METHOD [40-41]

Tractive energy consumption equations as derived in previous chapter can be optimized using various optimization techniques. There are various constraints available which need to be satisfied while optimizing the tractive energy consumption. So a constrained optimization technique will be required to optimize the above mentioned energy equation. Interior point algorithm is among such algorithms which are designed to solve the constrained optimization problems. This algorithm can optimize problems with both linear as well as non-linear constraints.

This algorithm can optimize large, sparse as well as small dense problems. It satisfies constraints/bounds at all iterations and can recover from infinity as well as not real/complex results. It is basically a large scale algorithm. An optimization algorithm is large scale when it uses linear algebra that does not need to store, nor operates on, full matrices.

In contrast, medium-scale methods internally create full matrices and use dense linear algebra. If a problem is sufficiently large, full matrices take up a significant amount of memory, and the dense linear algebra may require a long time to execute. In constrained optimization, the general aim is to transform the problem into an easier sub-problem that can then be solved and used as the basis of an iterative process. The basic approach in any algorithm which solves the non-linear constrained optimization problem is to solve a sequence of approximate minimization (optimization) problems. Interior point algorithm also uses the same basic approach. It converts the original problem into an approximate yet easy problem having properties similar to the original yet complex problem and then tries to optimize this approximate easy optimization problem.

Consider a problem defined by (5.1)

$$\min F(x) = 0 \text{ subject to } G(x) \leq 0 \text{ and } H(x) = 0 \quad (5.1)$$

where, G(x) and H(x) denotes the inequality and equality constraints respectively. For each λ > 0, the approximate problem is given by (5.2)

$$\min F_\lambda(x,p) = (\min F(x) - \lambda \textstyle\sum_i \ln p_i)$$

$$\text{subject to } G(x) + p = 0 \text{ and } H(x) = 0 \quad (5.2)$$

where λ is a parameter which changes after every iteration and p_i = number of slack variables and is equal to number of inequality constraints 'G' in the optimization problem. These stack variables are restricted to be positive to keep ln (p_i) bounded. As λ decreases to zero, the minimum of f_λ should correspond to the minimum of F. The added logarithmic term is called a barrier function. So basically, the original problem which has the inequality constraints given by (4.2) has been converted to a problem with equality constraints which is easier to solve. The added logarithmic term is called barrier function.

To solve the approximate problem, the algorithm uses one of two main types of steps at each iteration, which includes direct step and conjugate step. A direct step in (x, p) attempts to solve the Karush-Kuhn-Tucker (KKT) equations for the approximate problem via a linear approximation. This is also called Newton step. The direct step is taken first by default in this algorithm. If it cannot take direct step due to some problems, it attempts a CG step. The conjugate gradient approach to solving the approximate problem is similar to other conjugate gradient calculations.

In the case where algorithm takes conjugate step, the algorithm adjusts both x and p, keeping the slacks p positive. The approach is to minimize a quadratic approximation to the approximate problem in a trust region, subject to linearized constraints. For example, consider the case when the approximate problem is not locally convex near the current iteration, so the algorithm will not attempt direct step and will rather take a conjugate step.

In every iteration, the algorithm decreases a merit function. If either the nonlinear constraint function or objective function returns a complex value, infinite value or an error at an iterate k_j, the algorithm rejects this iterate k_j. For this to achieve, the objective function must have proper value at the starting point. This shows the significance of starting point. If the starting point is much far away from the actual solution, the algorithm may converge to a point which is far away from the optimum point and sometimes may return the infinite value. Then it will take time to reject that step and go for a different step which will increase the time of operation of algorithm which is not desired. So a valid starting point is must for the proper start and operation of interior point algorithm.

The rejection is equivalent to the case as if the merit function did not decrease sufficiently. In that case, the algorithm then attempts a different, shorter step. This process is repeated several times unless a desired solution is achieved. There are chances that result obtained is a local optima instead of a global optima i.e the algorithm may converge to a point which is not the actual solution. Toolbox of the algorithm is available in MATLAB 2010a.

5.2.1 Specifications of convergence for Interior point method

The convergence specifications of the algorithm are given in Table - 5.1.

TABLE 5.1 SPECIFICATIONS OF CONVERGENCE FOR INTERIOR POINT METHOD

Parameter	**Value**
Maximum Iterations	1000
Maximum functions evaluation	3000
Function Tolerance	10^{-6}
Non Linear Constraint tolerance	10^{-6}

5.3 ENERGY OPTIMIZATION USING INTERIOR POINT METHOD

5.3.1 Energy optimization for fixed gradient

Mathematical model of energy consumption as derived from speed-time curve is given by (3.13). This model is optimized under the following constraints:

a) Maximum velocity, V_m, attained by the train should not exceed a specified value.

b) Distance travelled by the train, S, remains constant.

The above mentioned constraints can be defined mathematically using the speed-time curve (fig. 3.3) and are given by (5.3) and (5.4)

$$\alpha t_1 \leq V_m \text{ ; } V_m = 50\text{m/s} \quad (5.3)$$

$$0.5\alpha t_1^2 + \alpha t_1 t_2 = S;\ S = 100 \text{ km} \quad (5.4)$$

Now under the above defined constraints, energy optimization of (3.14) - (3.16) has been done by Interior point algorithm. The optimized energy and corresponding parameters are shown in Table - 5.2

TABLE 5.2 OPTIMIZED PARAMETERS OBTAINED FOR FIXED GRADIENT USING INTERIOR POINT METHOD

Gradient → **Parameter ↓**	**Positive**	**Negative**	**Zero**
Acceleration ‘α’ (m/s^2)	0.2	0.3	0.1
Acceleration time ‘t_1’ (s)	200	225	359.7
Free Run Period ‘t_2’ (s)	2400	2000	2600
Energy Consumption (kWh)	680.8	503.4	565.6
No of Iterations	12	32	11

Fig. 5.1 shows the variation of function value for every iteration for positive gradient. It can be observed that the optimum point is achieved after 12^{th} iterations. Fig. 5.2 shows the constraint violation for every iteration for positive gradient.

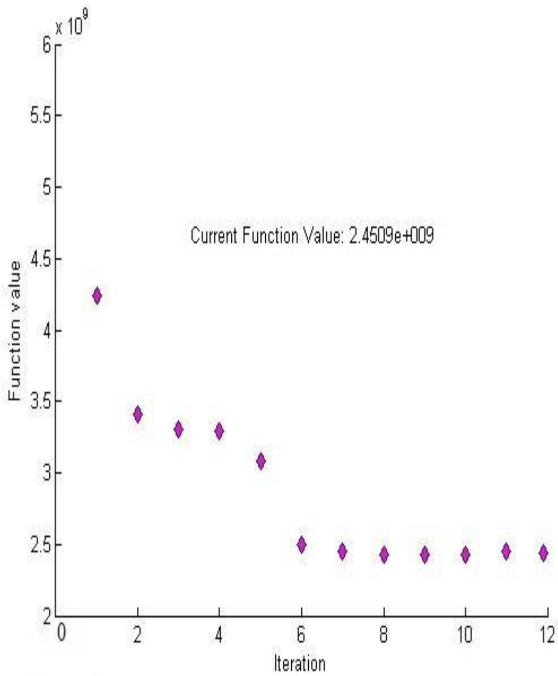

Fig. 5.1 Variation of function value for positive gradient using interior point method

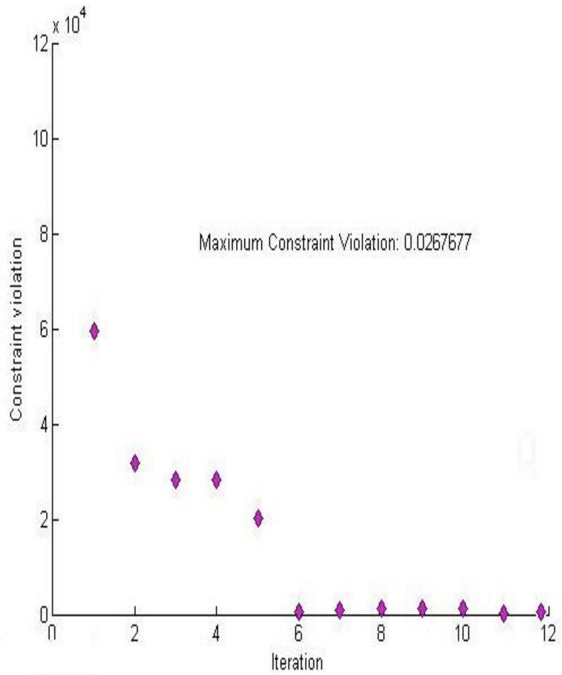

Fig. 5.2 Constraint violation for positive gradient using interior point method

Both the above plots are for positive gradient. Similar plots can be drawn for negative and zero gradients.

Fig. 5.3 shows the speed-time trajectory corresponding to optimized parameters for interior point method.

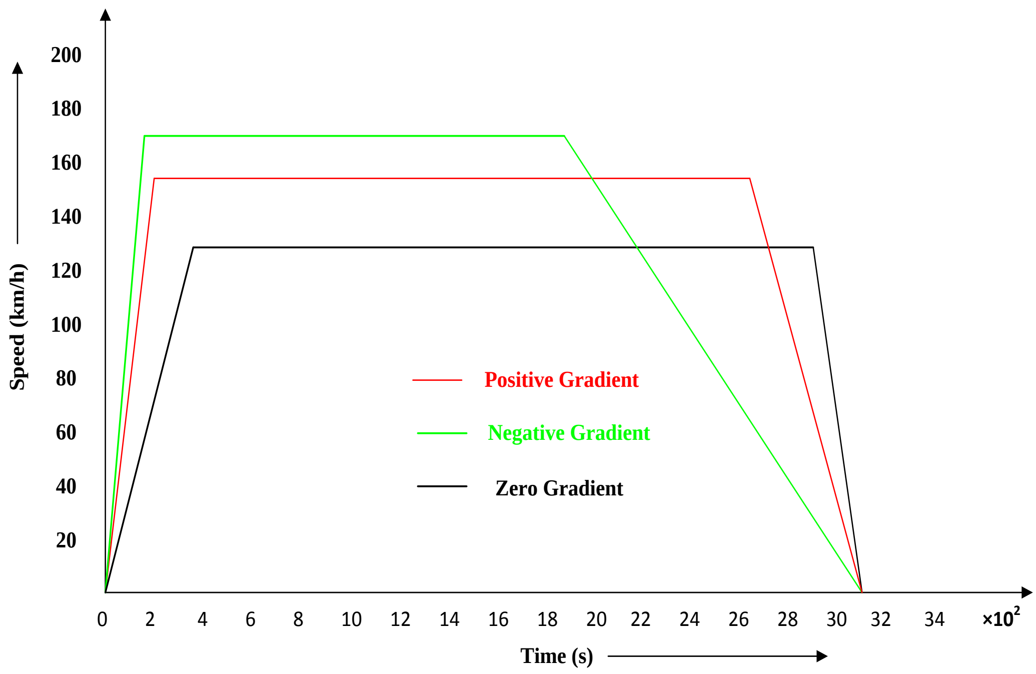

Fig. 5.3 Optimized speed-time trajectory for fixed gradient using interior point method

5.3.2 Energy optimization for variable gradient and fixed acceleration

Mathematical model of energy consumption as derived from speed-distance curve is given by (4.8) - (4.14). This equation is optimized using Interior point method under the constraints defined by the speed profile of the section (Table - 4.2). The optimized energy and corresponding parameters are given in Table - 5.3.

TABLE 5.3 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND FIXED ACCELERATION USING INTERIOR POINT METHOD

Parameter	Value
a_1 (m/s^2)	0.506
S_1 (m)	551
a_3 (m/s^2)	0.335
S_3 (m)	200
β_5 (m/s^2)	0.294
S_5 (m)	700
a_6 (m/s^2)	0.175
S_6 (m)	400
β_7 (m/s^2)	0.28
S_7 (m)	343
Total energy Consumption (kWh)	21.5
Total Time (min)	7.93

Fig. 5.4 shows the variation of function value for every iteration for sub section -1. Fig. 5.5 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

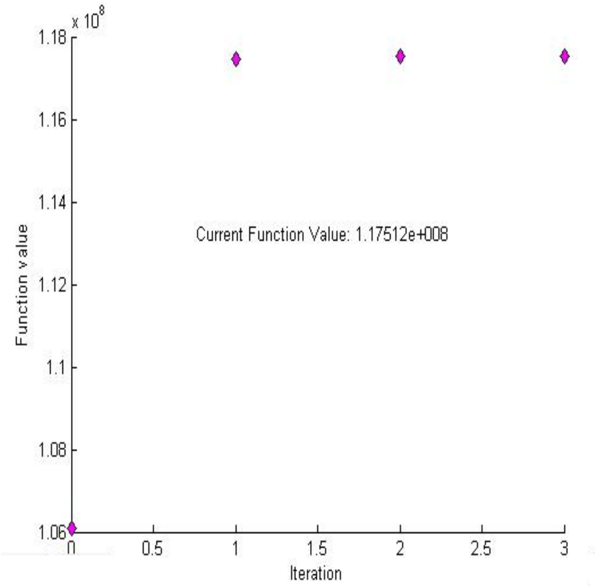

Fig. 5.4 Variation of function value for variable gradient and fixed acceleration using interior point method

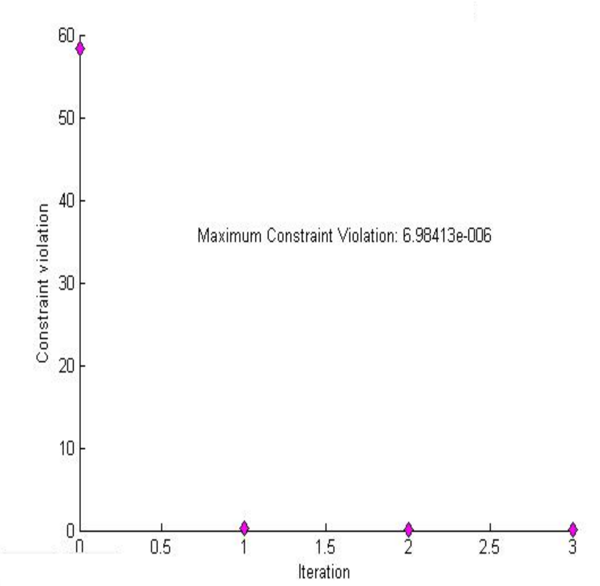

Fig. 5.5 Constraint violation for variable gradient and fixed acceleration using interior point method

Fig. 5.6 shows the speed-distance trajectory corresponding to optimized parameters for interior point method.

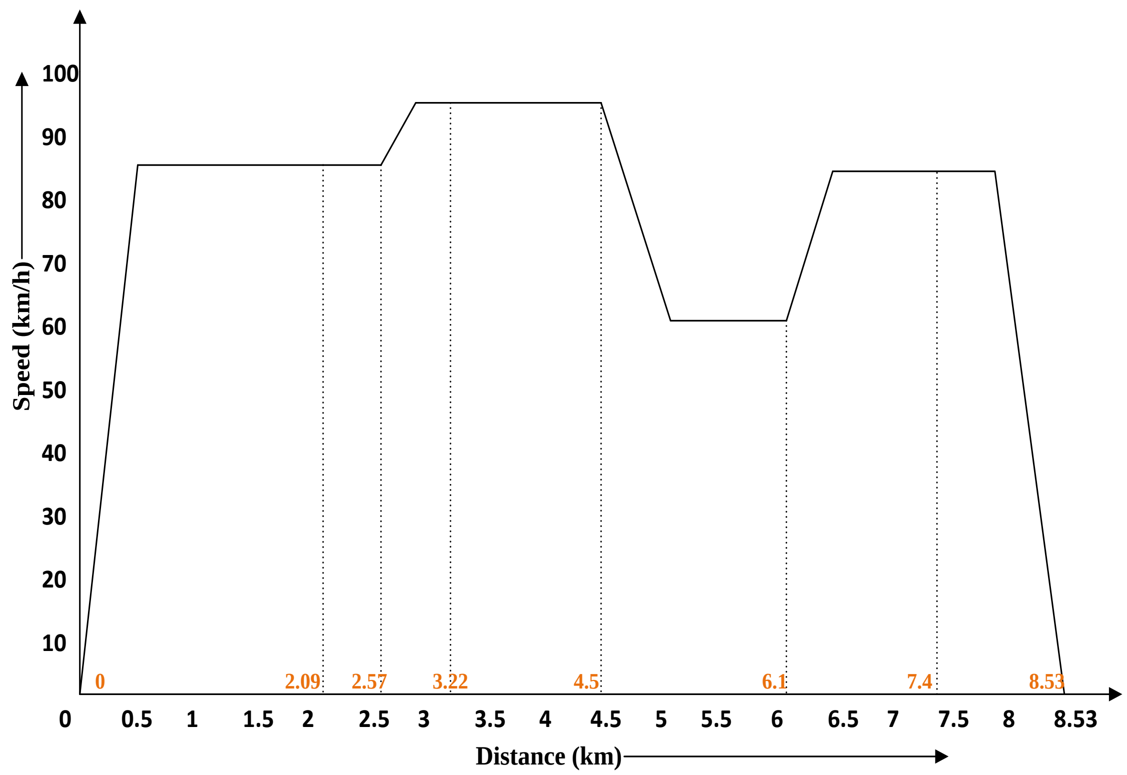

Fig. 5.6 Optimized speed- distance trajectory for variable gradient and fixed acceleration using interior point method

5.3.3 Energy optimization for variable gradient and variable acceleration

Mathematical model of energy consumption as derived from speed-distance curve is given by (4.16) - (4.22). This equation is optimized under the constraints defined by the speed profile of the section (Table - 4.2). The optimized energy and corresponding parameters are given in Table - 5.4.

TABLE 5.4 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION USING INTERIOR POINT METHOD

Parameter	**Value**
a_{1a} (m/s^2)	0.4
S_{1a} (m)	344.8
a_{1b} (m/s^2)	0.3
S_{1b} (m)	504.4
a_{3a} (m/s^2)	0.22
S_{3a} (m)	318.18
a_{3b} (m/s^2)	0.1507
S_{3b} (m)	165.9
β_{5a} (m/s^2)	0.3
S_{5a} (m)	269.1
β_{5b} (m/s^2)	0.55
S_{5b} (m)	299.7
a_{6a} (m/s^2)	0.3
S_{6a} (m)	213.33
a_{6b} (m/s^2)	0.16
S_{6b} (m)	193.3
β_{7a} (m/s^2)	0.21
S_{7a} (m)	188.1
β_{7b} (m/s^2)	0.34
S_{7b} (m)	688.14
Total energy Consumption (kWh)	23.4
Total Time (min)	8.2

Fig. 5.7 shows the variation of function value for every iteration for sub section -1. Fig. 5.8 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

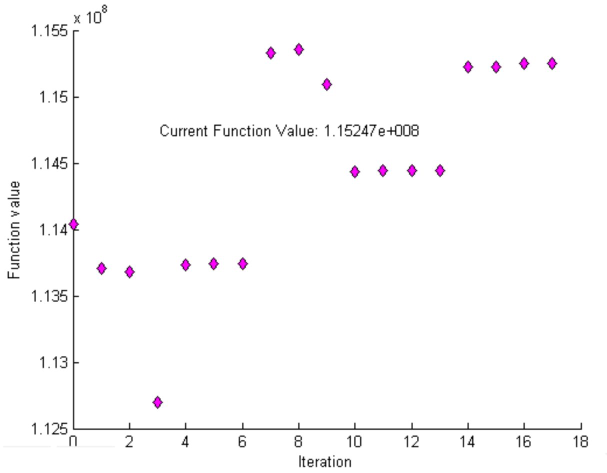

Fig. 5.7 Variation of function value for variable gradient and variable acceleration using interior point method

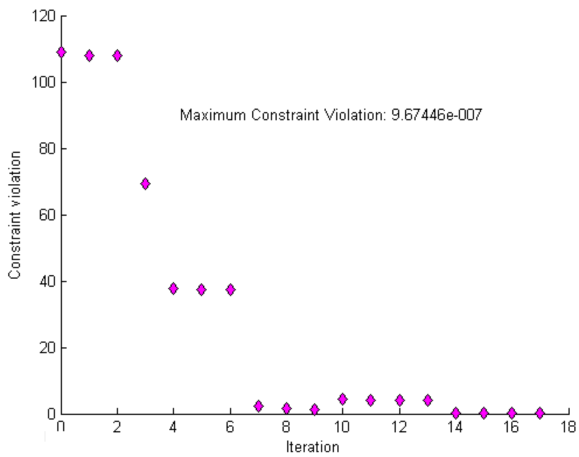

Fig. 5.8 Constraint violation for variable gradient and variable acceleration using interior point method

Fig. 5.9 shows the speed-distance trajectory corresponding to optimized parameters for interior point method.

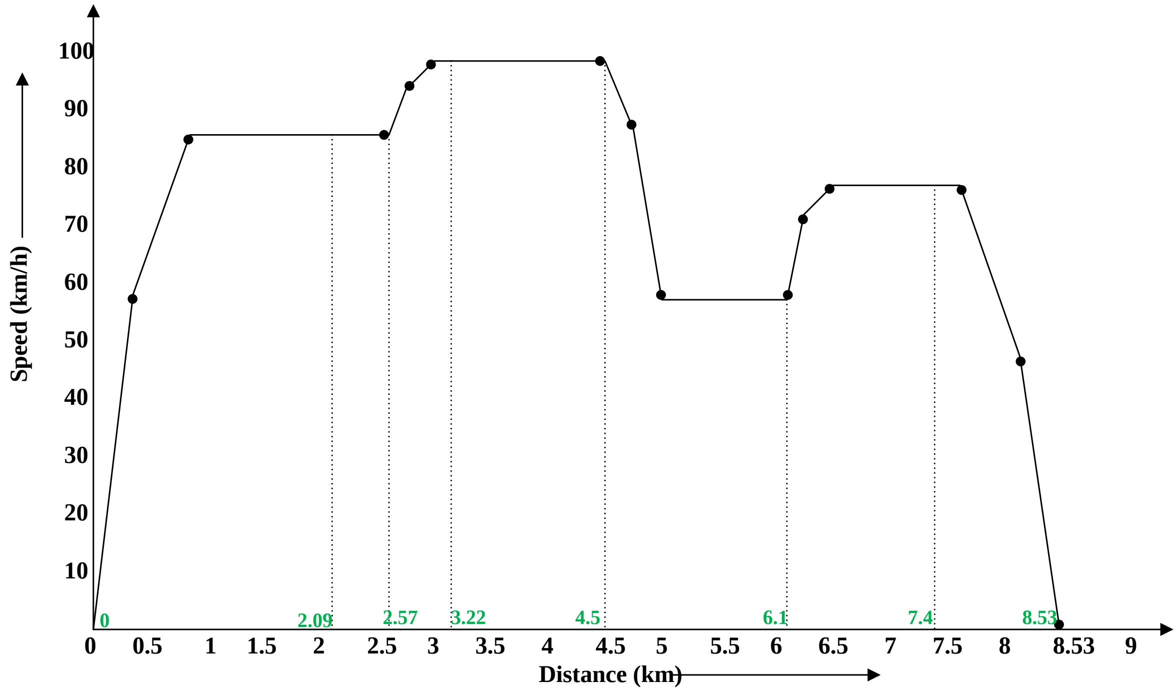

Fig. 5.9 Optimized speed- distance trajectory for variable gradient and variable acceleration using interior point method

5.4 PATTERN SEARCH METHOD [37-38]

Pattern search (PS) is among the family of numerical optimization methods that do not require the derivative of the problem to be optimized. Hence Patten Search can be used on functions that are not continuous or differentiable. As there is no need to find derivatives which further reduces the complexity of the method. Such optimization methods are also known as direct-search, derivative-free, or black-box methods. The name, pattern search, was coined by Hooke and Jeeves.

Pattern-search finds a sequence of points, x0, x1, x2, ... , that approach an optimal point. The value of the objective function either decreases or remains the same from each point in the sequence to the next. Pattern search mainly takes two input arguments (objective function and starting point). Instead of searching in the random directions like random search methods (univariate method) it searches for the optimal solution in fixed directions called pattern directions. Thus it's a fast method as compared to other conventional methods.

The pattern search algorithm uses the Augmented Lagrangian Pattern Search (ALPS) algorithm to solve nonlinear constraint problems. The optimization problem solved by the ALPS algorithm is defined by (5.5) – (5.8)

$$\text{Min} \quad f(x) \text{ such that} \tag{5.5}$$

$$c_i(x) \leq 0 \text{ ; } i = 1\ldots\ldots m; \tag{5.6}$$

$$ceq_i(x) = 0; \text{ I} = m+1\ldots\ldots m_t \tag{5.7}$$

$$lb \leq x \leq ub; \tag{5.8}$$

where c(x) represents the nonlinear inequality constraints, ceq(x) represents the equality constraints, m is the number of nonlinear inequality constraints, m_t is the total number of nonlinear constraints and lb and ub represents lower and upper bounds respectively.

The ALPS algorithm attempts to solve a nonlinear optimization problem with nonlinear constraints, linear constraints, and bounds. In this approach, bounds and linear constraints are handled separately from nonlinear constraints. As already explained, all conventional methods attempt to solve an approximate easy problem which is derived from the original complex problem. Pattern Search also follows the same rule.

A sub-problem is formulated by combining the objective function and nonlinear constraint function using the Lagrangian and the penalty parameters. A sequence of such optimization problems are approximately minimized using a pattern search algorithm such that the linear constraints and bounds are satisfied. Each sub-problem solution represents one iteration. The number of function evaluations per iteration is therefore much higher when using nonlinear constraints than otherwise.

A subproblem formulation is defined by (5.9)

$$\Theta(x,\lambda,s,\rho) = f(x) - \sum_{i=1}^{m} \lambda_i s_i \log(s_i - c_i(x)) + \sum_{i=m+1}^{m_t} \lambda_i ceq_i(x) + \frac{\rho}{2} \sum_{i=m+1}^{m_t} ceq_i(x)^2 \tag{5.9}$$

where, the components λ_i of the vector λ are nonnegative and are known as Lagrange multiplier estimates, the elements s_i of the vector s are nonnegative shifts and ρ is the positive penalty parameter.

The algorithm begins by using an initial value for the penalty parameter (Initial Penalty).

The pattern search minimizes a sequence of subproblems, each of which is an approximation of the original problem. Each subproblem has a fixed value of λ, s, and ρ. When the subproblem is minimized to a required accuracy and satisfies feasibility conditions, the Lagrangian estimates are updated. Otherwise, the penalty parameter is increased by a penalty factor.

This results in a new sub-problem formulation and minimization problem. These steps are repeated until the stopping criteria are met. Each sub-problem solution represents one iteration. The number of function evaluations per iteration is therefore much higher when using nonlinear constraints than otherwise. Direct search methods require many function evaluations as compared to derivative-based optimization methods. The pattern search algorithm can quickly find the neighbourhood of an optimum point, but may be slow in detecting the minimum itself. This is the cost of not using derivatives. The pattern search solver can reduce the number of function evaluations using an accelerator.

This method also requires a proper starting point which leads to the feasible solution in effective time. If the strating point is very far away from actual solution, the algorithm may take very much time in converging to the optimal solution although there are less yet possible chances to converge to local optimum as compared to Interior point method. The pattern search algorithm is robust in relation to objective function failures. Pattern Search tolerates function evaluations resulting in Infinite or complex values. When the objective function at the initial point x0 is a real, finite value, pattern-search treats poll point failures as if the objective function values are large, and ignores them. Tool box of pattern search method is available in MATLAB 2010a.

5.4.1 Specifications of convergence for pattern search method

The convergence specifications for pattern search method are given in Table - 5.5.

TABLE 5.5 SPECIFICATIONS OF CONVERGENCE FOR PATTERN SEARCH METHOD

Parameter	**Value**
Maximum Iterations	300
Maximum functions evaluation	6000
Function Tolerance	10^{-6}
Non Linear Constraint tolerance	10^{-6}

5.5 ENERGY OPTIMIZATION USING PATTERN SEARCH METHOD

5.5.1 Energy optimization for fixed gradient

Mathematical model of energy consumption as derived from speed-time curve is given by (3.14) - (3.16). This model is optimized under the constraints defined by (5.3) - (5.4). The optimized energy and corresponding parameters are shown in Table - 5.6

TABLE 5.6 OPTIMIZED PARAMETERS OBTAINED FOR FIXED GRADIENT USING PATTERN SEARCH METHOD

Gradient → **Parameter ↓**	**Positive**	**Negative**	**Zero**
Acceleration ‘α’ (m/s^2)	0.23	0.28	0.16
Acceleration time ‘t_1’ (s)	204.1	160	299.8
Free Run Period ‘t_2’ (s)	2152	1941	2457
Energy Consumption (kWh)	670	491.7	564.9
No of Iterations	13	17	7

Fig. 5.10 shows the variation of function value for every iteration for positive gradient. It can be observed that the optimum point is achieved after 13^{th} iterations. Fig. 5.11 shows the constraint violation for every iteration for positive gradient.

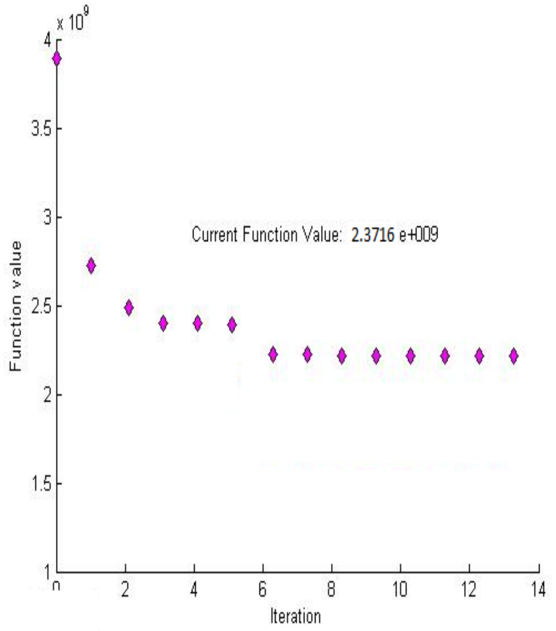

Fig. 5.10 Variation of function value for positive gradient using pattern search method

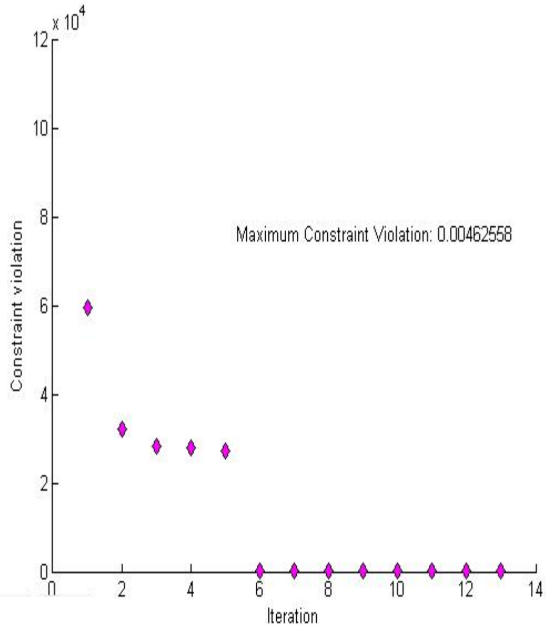

Fig. 5.11 Constraint violation for positive gradient using pattern search method

Both the above plots are for positive gradient. Similar plots can be drawn for negative and zero gradients.

Fig. 5.12 shows the speed-time trajectory corresponding to optimized parameters for pattern search method.

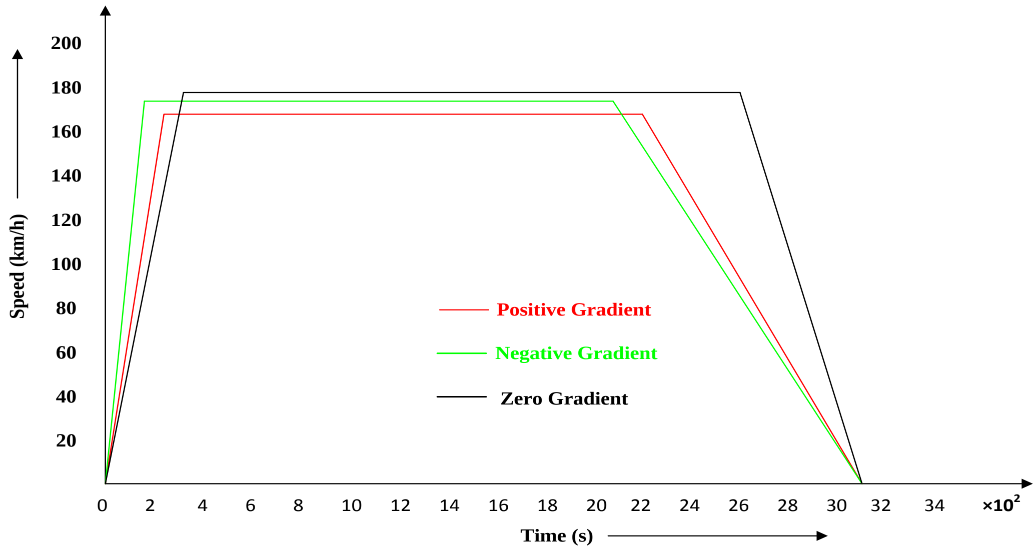

Fig. 5.12 Optimized speed-time trajectory for fixed gradient using pattern search method

5.5.2 Energy optimization for variable gradient and fixed acceleration

Mathematical model of energy consumption as derived from speed-distance curve is given by (4.8) - (4.14). This equation is optimized by pattern search method under the constraints defined by the speed profile of the section (Table - 4.2). The optimized energy and corresponding parameters are given in Table - 5.7.

TABLE 5.7 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND FIXED ACCELERATION USING PATTERN SEARCH METHOD

Parameter	**Value**
a_1 (m/s^2)	0.505
S_1 (m)	551
a_3 (m/s^2)	0.26
S_3 (m)	250
β_5 (m/s^2)	0.294
S_5 (m)	700
a_6 (m/s^2)	0.17
S_6 (m)	400
β_7 (m/s^2)	0.286
S_7 (m)	400
Total energy Consumption (kWh)	23.8
Total Time (min)	7.96

Fig. 5.13 shows the variation of function value for every iteration for sub section -1. Fig. 5.14 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

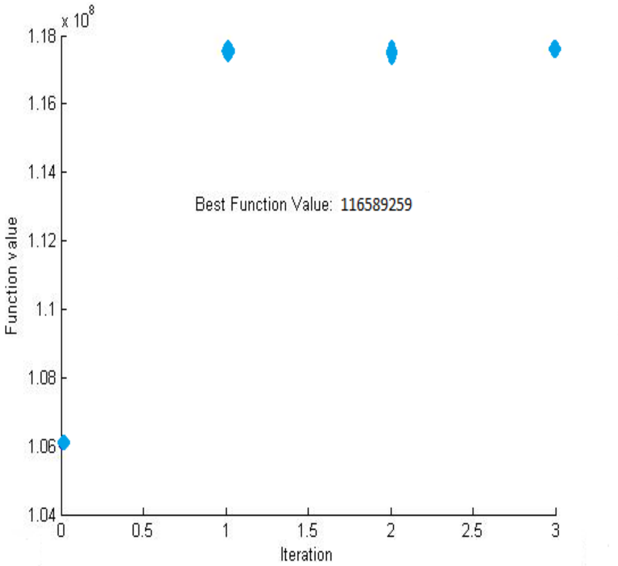

Fig. 5.13 Variation of function value for variable gradient and fixed acceleration using pattern search method

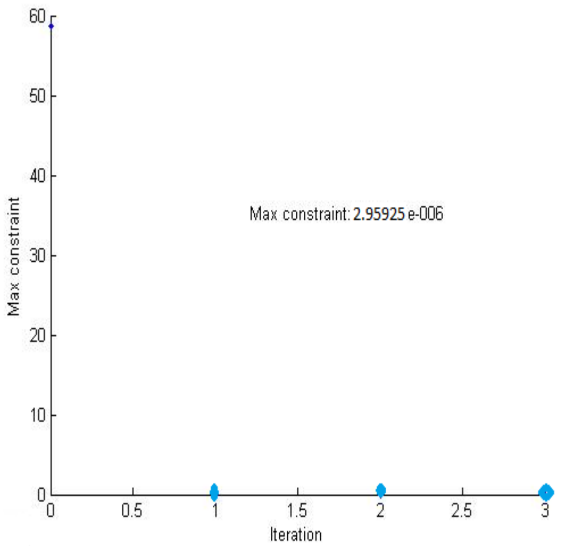

Fig. 5.14 Constraint violation for variable gradient and fixed acceleration using pattern search method

Fig. 5.15 shows the speed-distance trajectory corresponding to optimized parameters for pattern search method.

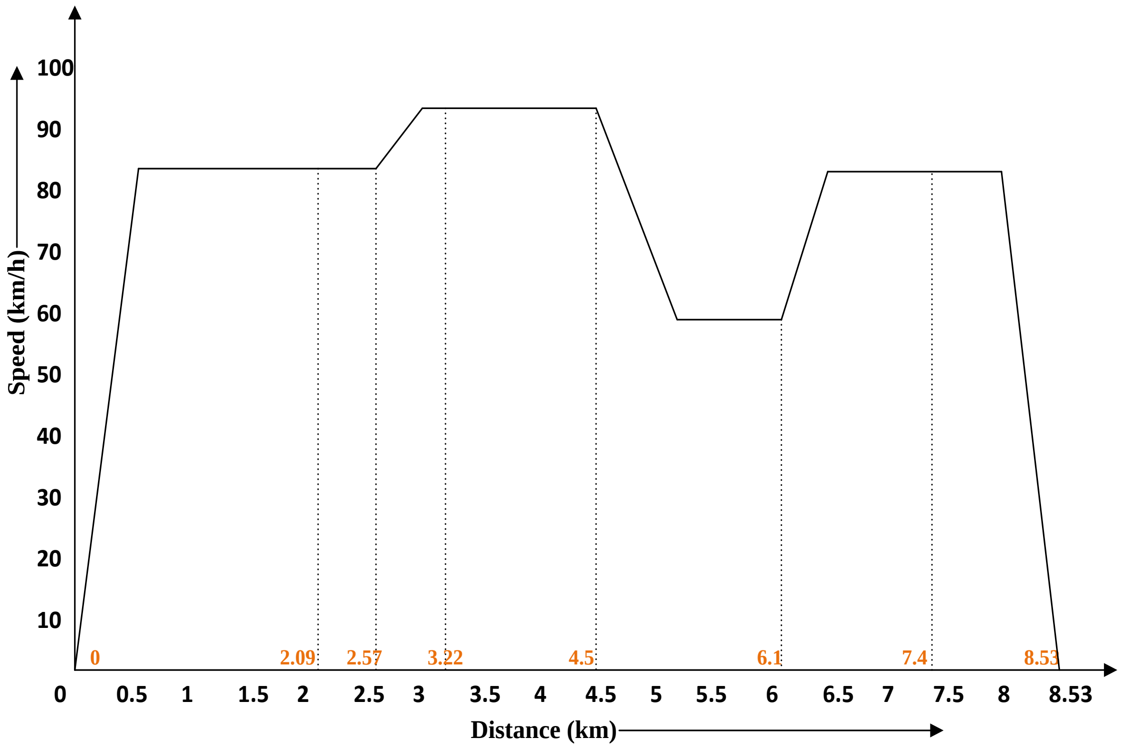

Fig. 5.15 Optimized speed- distance trajectory for variable gradient and fixed acceleration using pattern search method

5.5.3 Energy optimization for variable gradient and variable acceleration

Equation of energy consumption as derived from speed-distance curve is given by (4.16) - (4.22). This equation is optimized under the constraints defined by the speed profile of the section (Table - 4.2). The optimized energy and corresponding parameters are given in Table – 5.8.

TABLE 5.8 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION USING PATTERN SEARCH METHOD

Parameter	**Value**
a_{1a} (m/s^2)	0.35
S_{1a} (m)	344.7
a_{1b} (m/s^2)	0.18
S_{1b} (m)	815.7
a_{3a} (m/s^2)	0.29
S_{3a} (m)	242.2
a_{3b} (m/s^2)	0.11
S_{3b} (m)	216.3
β_{5a} (m/s^2)	0.14
S_{5a} (m)	554.7
β_{5b} (m/s^2)	0.22
S_{5b} (m)	666.1
a_{6a} (m/s^2)	0.3
S_{6a} (m)	213.33
a_{6b} (m/s^2)	0.2
S_{6b} (m)	160
β_{7a} (m/s^2)	0.19
S_{7a} (m)	93.65
β_{7b} (m/s^2)	0.35
S_{7b} (m)	783.6
Total energy Consumption (kWh)	23.27
Total Time (min)	8.6

Fig. 5.16 shows the variation of function value for every iteration for sub section -1 and Fig. 5.17 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

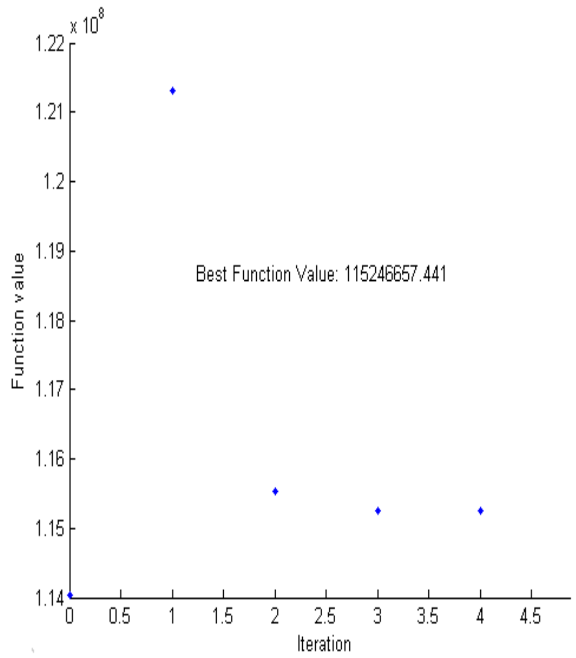

Fig. 5.16 Variation of function value for variable gradient and variable acceleration using pattern search method

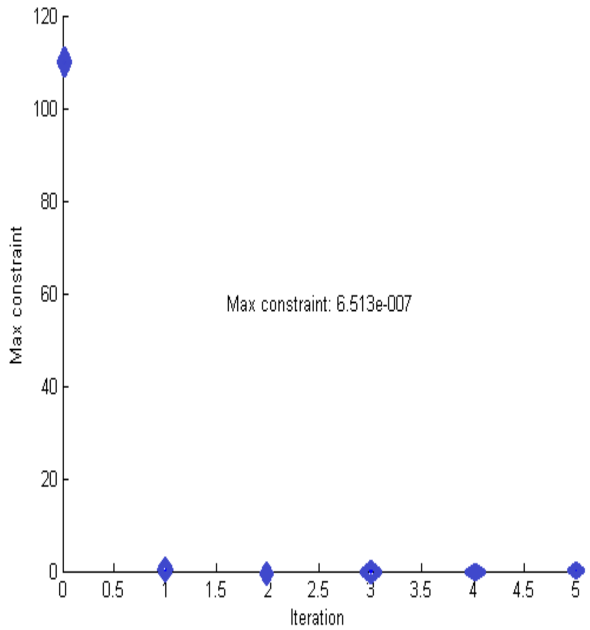

Fig. 5.17 Constraint violation for variable gradient and variable acceleration using pattern search method

Fig. 5.18 shows the speed-distance trajectory corresponding to optimized parameters for pattern search.

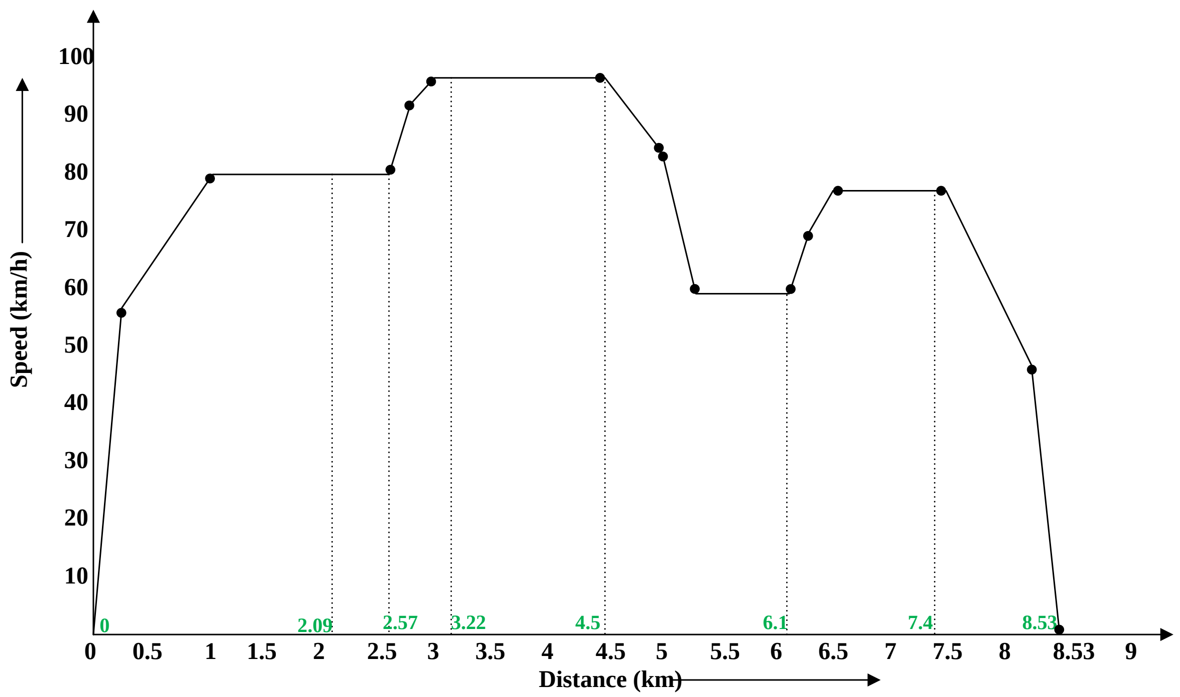

Fig. 5.18 Optimized speed-distance trajectory for variable gradient and variable acceleration using pattern search method

5.6 CONCLUSION

This chapter presents the various conventional optimization methods. Optimization of energy consumption derived using both speed-time curve and speed-distance curve has been done using these conventional methods and the graph of function value and constraint violations has been plotted with iteration number. Further, optimized speed-time and speed-distance trajectories are plotted. It has been observed that pattern search method provides better results.

CHAPTER 6

INTELLIGENT AND EVOLUTIONARY TECHNIQUES FOR OPTIMIZATION

GENERAL

Conventional methods are used for energy optimization in previous chapter. Most of the conventional optimization methods (direct search or gradient search methods) have a common characteristic that they all work by point-by-point basis. An algorithm starts with an initial point (usually supplied by the user) and depending on the transition rule used in the algorithm a new point is determined. The algorithms vary according to the transition rule updates the initial point and a new point is obtained. But there is one limitation with conventional methods as most of these optimization methods are suitable for well-behaved, unimodal, simple objective functions.

A unimodal function is one that has only one peak (maximum) or valley (minimum) in a given interval. Thus a function of one variable is said to be unimodal if, given that two values of the variable are on the same side of the optimum, the one nearer the optimum gives the better functional value (i.e., the smaller value in the case of a minimization problem). When applied to multimodal problems or problems where derivative information is not available, most of these methods either can't be used or not very efficient. This suggests that in order to solve complex, multimodal, discrete or discontinuous problems, better methods are required. This chapter presents the evolutionary and intelligent techniques of optimization. There are various intelligent optimization techniques like Genetic Algorithm (GA), Simulated Annealing (SA), Differential Evolution (DE), Ant Colony Optimization, Particle Swarm Optimization (PSO) etc. Each method differs from the other in the way it handles the problem.

In this work, Genetic algorithm and Particle swarm optimization is used to optimize the equation of energy consumption as already derived in chapter 3 and 4. Various constraints available during motion of the train are taken into account.

6.2 GENETIC ALGORITHM [44-46]

Genetic algorithm is an exploratory method in the field of artificial intelligence which locates a near optimal solution to complex problems. It mimics some of the processes observed in natural evolution. Unlike other calculus methods, there is no derivative/slope is required in GA. So, there are very less chances that GA gets trapped to a local optima. Further, if the search space is very large then GA can provide better results. Another advantage of genetic algorithm is that they constitute a parallel search of the solution space, as opposed to a point-by-point search. By using a population of trial solutions, the genetic algorithm can effectively explore many regions of the search space simultaneously, rather than a single region. This is one of the reasons why Genetic algorithm is less sensitive to local minima.

A genetic algorithm is an exploratory procedure that is often able to locate near optimal solutions to complex problems. To do this, it maintains a set of trial solutions (often called individuals), and forces them to "evolve" towards an acceptable solution. First, a representation for possible solutions must be developed. Then, starting with an initial random population and employing survival of- the fittest and exploiting old knowledge in the gene pool, each generation's ability to solve the problem should improve. This is achieved through a four-step process involving evaluation, reproduction, recombination, and mutation. It generates solution on the basis of the techniques inspired by natural evolution, such as inheritance, selection, crossover and mutation.

First, a representation of possible solutions must be developed. Initially, a random population is used to start the process and based on the "survival of the fittest", the best fit function is selected to move towards optimal solution. The steps include evaluation, reproduction, recombination and mutation.

a) Representation: Representation is the basic step before applying GA. Here, a computer compatible representation or encoding is developed. These representations are also termed as 'chromosomes'. Generally, a binary string is used for representation. The most common representation is a binary string, where sections of the string represent encoded parameters of the solution. Accuracy of the solution depends upon the number of digits assigned.

b) Evaluation: This is the first step in each generation to evaluate the current chromosomes. Here, each chromosome is decoded, evaluated and it's fitness is decided. Interpretation of the chromosomes is used here only. Each chromosome is decoded here and it's fitness is measured. This fitness measure decides the number of off-springs which will be generated from each chromosome.

c) Reproduction: In this step, based upon the evaluation of current one a new population is created. Each chromosome generates copies of it while the best fit chromosome has the most number of copies. Survival of the fittest strategy is applied here. There are many ways to calculate the number of offspring's generated by each chromosome. The two most popular method includes ratioing and ranking.

In ratioing, offspring's are produced as per the fitness value of each individual. So the individual having better fitness value will generate more number of offspring's. The disadvantage of ratioing is that the problem may converge to a premature sub-optimal solution. GA is based on the fact that genetic material is never lost but preserved in the population as a whole. This assumption is also not met when an individual is allowed to dominate the problem.

Another way is ranking. The number of offspring's generated by an individual depends upon the ranking of individual in population. In this method, no one individual can dominate the problem. The primary disadvantage of ranking is speed because better chromosomes are not capable of guiding the population easily. This forces good answers to develop more slowly.

d) Recombination: In the earlier step, population is created. In this population, there are many offspring's which are similar to each other as reproduction simply produces the multiple copies of existing chromosomes. In this step, copies of chromosomes created in the reproduction are combined and new chromosomes are produced. These new chromosomes carry most of the features of the previous ones as they are produced with the recombination of them. Crossover technique is employed for reproduction. In crossover, two chromosomes are selected and randomly swapped about a crossover point. There are various methods of crossover like one-point crossover, two-point crossover etc.

In One-point crossover, A single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. The resulting organisms are the children. In two-point crossover, two points are selected on parent's chromosome. All data beyond that point in either organism string is swapped between the two parent organisms.

e) Mutation: This is the last step. It takes care of the fact that initial selected population may not contain all the information required to solve the given problem. Also, the individuals that haven't produced any offspring may contain some information required to solve the problem. To accommodate this, mutation is done which basically injects new information into the population. This is usually done by changing a fixed number of bits in every generation. In mutation, the new solution obtained may be entirely different from the previous solution. Hence there is possibility that GA can come to a better solution by using mutation.

f) GA Parameters The best values for mutation rate, crossover percentage, and other parameters are problem specific. If the population is too small, relative to the size of the search space, it will be difficult to effectively search the entire region. Second, large mutation rates tend to disrupt the steady improvement resulting from crossover and reproduction. It has been observed through researches that a population of 30 individuals, a crossover probability of 60%, and a mutation probability of 3% seems to be a good starting point. GA toolbox is available in MATLAB.

6.2.1 Specifications of Convergence for Genetic Algorithm

The convergence specifications of the algorithm are given in Table - 6.1.

TABLE 6.1 SPECIFICATIONS OF CONVERGENCE FOR GENETIC ALGORITHM

Parameter	Value
Generation	100
Time limit	Infinite
Fitness limit	-(infinite)
Stall Generations	50
Stall Time Limit	Infinite
Function tolerance	10^{-6}
Non linear constraint tolerance	10^{-6}

6.3 ENERGY OPTIMIZATION USING GENETIC ALGORITHM

6.3.1 Energy optimization for fixed gradient

Mathematical model of energy consumption as derived from speed-time curve is given by (3.14) - (3.16). This model is now optimized by genetic algorithm under the constraints defined by (5.3) - (5.4).

The optimized energy and corresponding parameters are shown in Table - 6.2

TABLE 6.2 OPTIMIZED PARAMETERS OBATAINED FOR FIXED GRADIENT USING GENETIC ALGORITHM

Gradient → Parameter ↓	Positive	Negative	Zero
Acceleration ‘α’ (m/s^2)	0.35	0.2	0.5
Acceleration time ‘t_1’ (s)	110.3	221.6	85.3
Free Run Period ‘t_2’ (s)	2871.3	2751.8	2481
Energy Consumption (kWh)	667.2	437.4	563.8
No of Iterations	96	73	85

Fig. 6.1 shows the variation of function value for every iteration for positive gradient. It can be observed that the optimum point is achieved after 96^{th} iterations. Fig. 6.2 shows the constraint violation for every iteration for positive gradient.

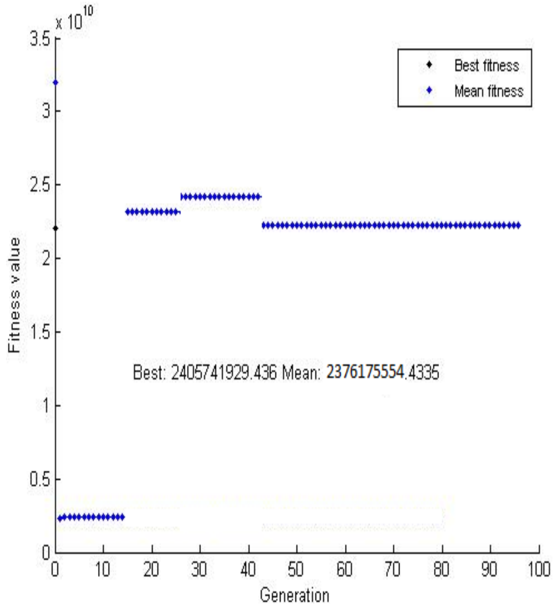

Fig. 6.1 Variation of function value for positive gradient using genetic algorithm

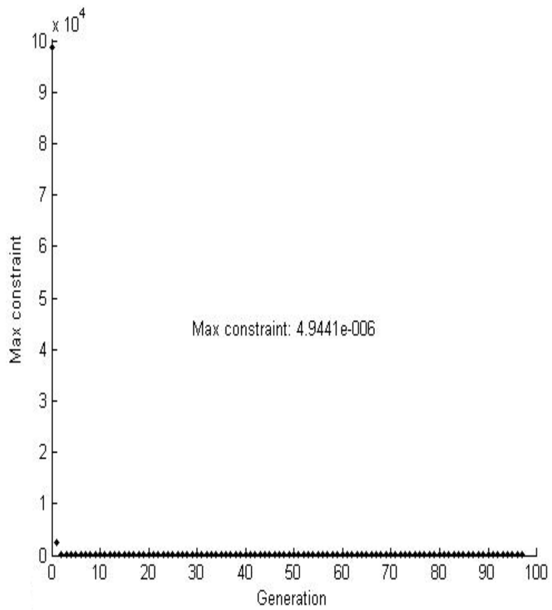

Fig. 6.2 Constraint violation for positive gradient using genetic algorithm

Both the above plots are for positive gradient. Similar plots can be drawn for negative and zero gradients. Fig. 6.3 shows the speed-time trajectory corresponding to optimized parameters for genetic algorithm.

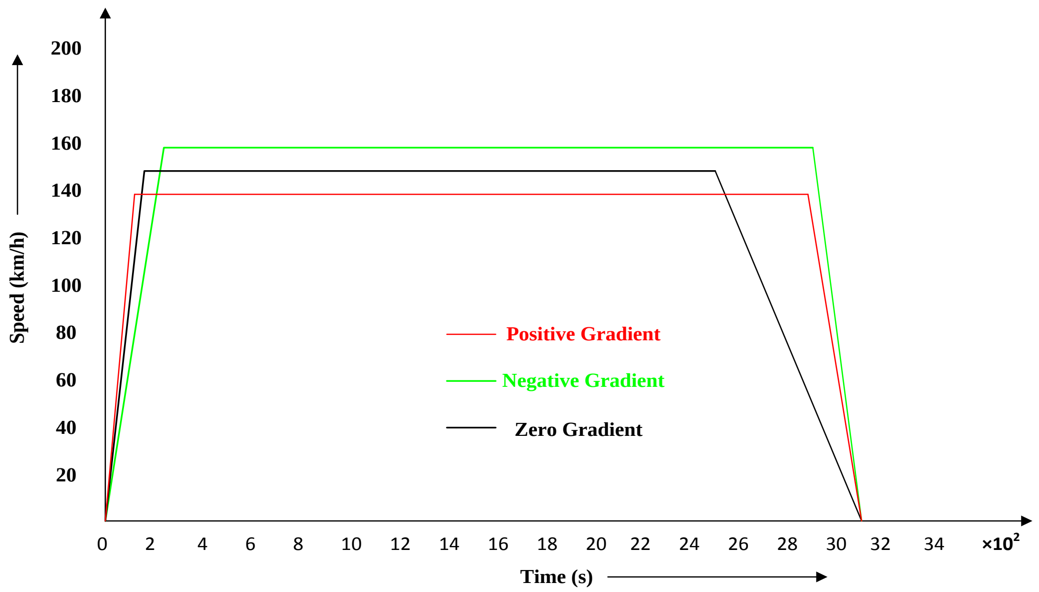

Fig. 6.3 Optimized speed-time trajectory for fixed gradient using genetic algorithm

6.3.2 Energy optimization for variable gradient and fixed acceleration

Equation of energy consumption as derived from speed-distance curve is given by (4.8) - (4.14). This equation is optimized using Genetic Algorithm under the constraints defined by the speed profile of the section (Table - 4.2). The optimized energy and corresponding parameters are given in Table - 6.3

TABLE 6.3 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND FIXED ACCELERATION USING GENETIC ALGORITHM

Parameter	**Value**
a_1 (m/s^2)	0.43
S_1 (m)	656.4
a_3 (m/s^2)	0.54
S_3 (m)	120
β_5 (m/s^2)	0.2
S_5 (m)	1181.3
a_6 (m/s^2)	0.175
S_6 (m)	400
β_7 (m/s^2)	0.25
S_7 (m)	320
Total energy Consumption (kWh)	23.7
Total Time (min)	8.03

Fig. 6.4 shows the variation of function value for every iteration for sub section -1. Fig. 6.5 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

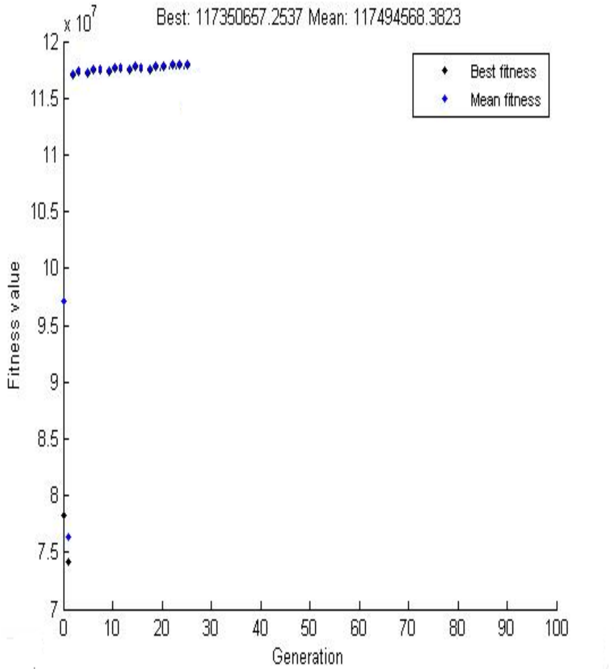

Fig. 6.4 Variation of function value for variable gradient and fixed acceleration using genetic algorithm

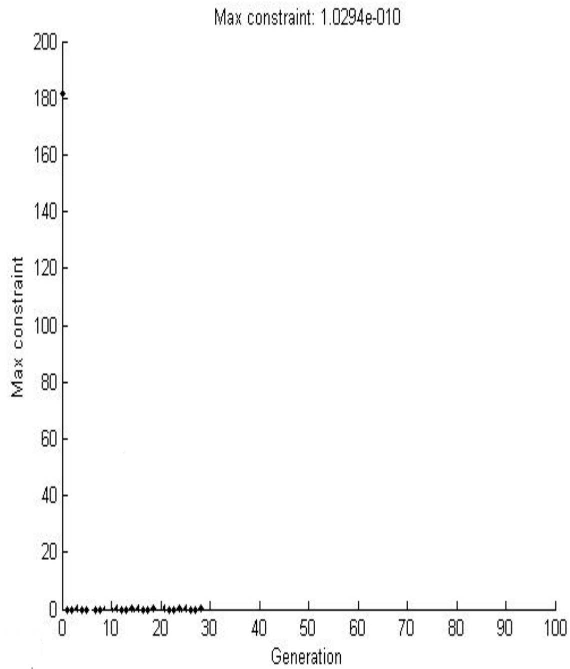

Fig. 6.5 Constraint violation for variable gradient and fixed acceleration using genetic algorithm

Fig. 6.6 shows the speed-distance trajectory corresponding to optimized parameters for interior point method.

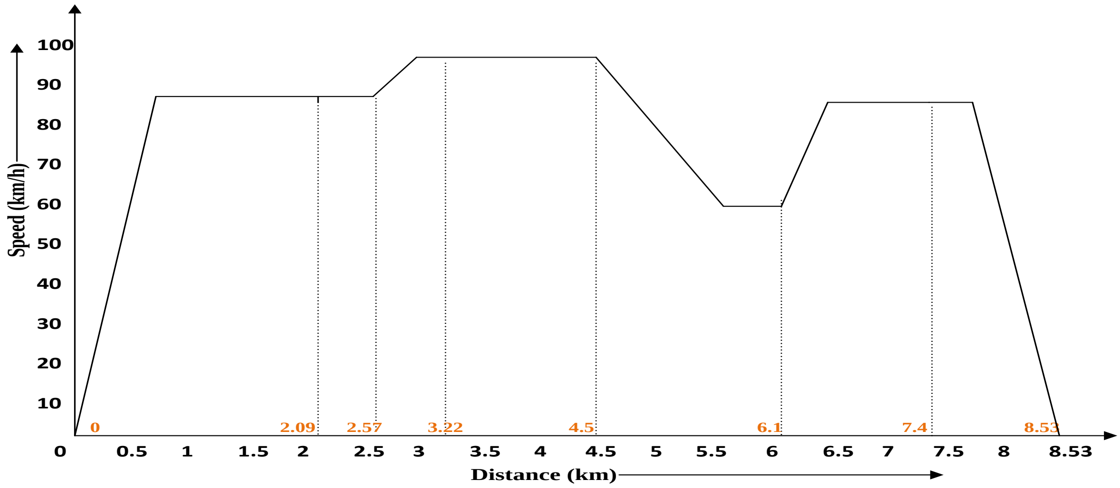

Fig. 6.6 Optimized speed-distance trajectory for variable gradient and fixed acceleration using genetic algorithm

6.3.3 Energy optimization for variable gradient and variable acceleration

Equation of energy consumption as derived from speed-distance curve is given by (4.16) - (4.22). This equation is optimized under the constraints defined by Table - 4.2. The optimized energy and corresponding parameters are given in Table - 6.4.

TABLE 6.4 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION USING GENETIC ALGORITHM

Parameter	**Value**
a_{1a} (m/s^2)	0.4
S_{1a} (m)	276.7
a_{1b} (m/s^2)	0.3
S_{1b} (m)	530.8
a_{3a} (m/s^2)	0.32
S_{3a} (m)	216.6
a_{3b} (m/s^2)	0.12
S_{3b} (m)	216.1
β_{5a} (m/s^2)	018
S_{5a} (m)	441.4
β_{5b} (m/s^2)	0.25
S_{5b} (m)	583.6
a_{6a} (m/s^2)	0.3
S_{6a} (m)	227.4
a_{6b} (m/s^2)	0.19
S_{6b} (m)	166.2
β_{7a} (m/s^2)	0.21
S_{7a} (m)	193.4
β_{7b} (m/s^2)	0.38
S_{7b} (m)	707.2
Total energy Consumption (kWh)	23.02
Total Time (min)	8.35

Fig. 6.7 shows the variation of function value for every iteration for sub section -1 and Fig. 6.8 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

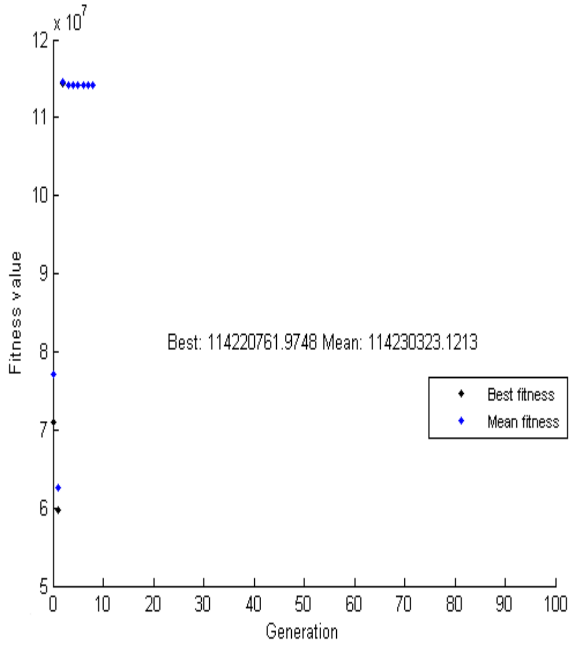

Fig. 6.7 Variation of function value for variable gradient and variable acceleration using genetic algorithm

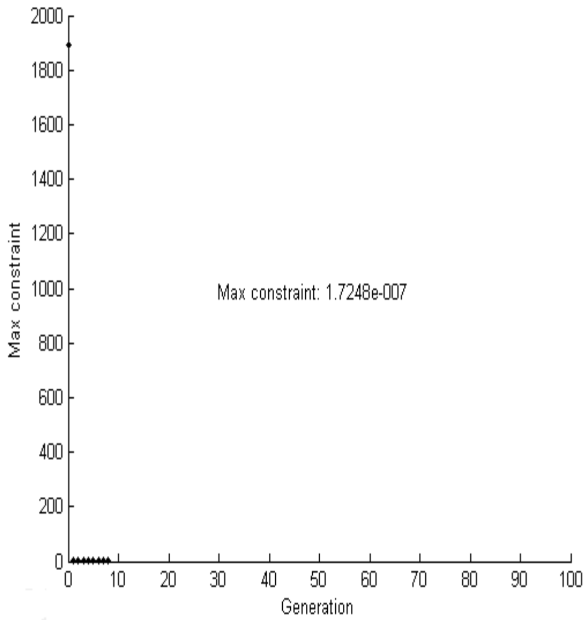

Fig. 6.8 Constraint violation for variable gradient and variable acceleration using genetic algorithm

Fig. 6.9 shows the speed-distance trajectory corresponding to optimized parameters for interior point method.

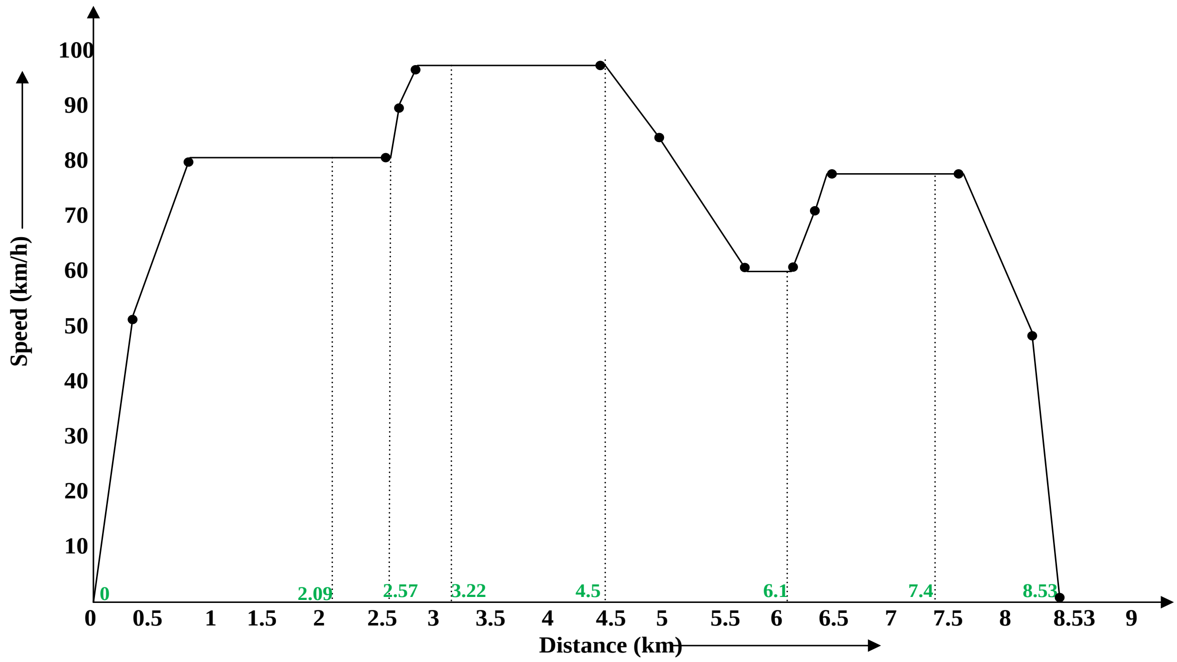

Fig. 6.9 Optimized speed- distance trajectory for variable gradient and variable acceleration using genetic algorithm

6.4 PARTICLE SWARM OPTIMIZATION (PSO) [47-48]

Particle Swarm Optimization is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity.

PSO is similar to a genetic algorithm (GA) in that the system is initialized with a population of random solutions It is unlike a GA, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, are then “flown” through the problem space.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another “best” value that is tracked by the global version of the particle swarm optimizer is the overall best value, and its location, obtained so far by any particle in the population. This location is called gbest. The particle swarm optimization concept consists of, at each time step, changing the velocity (accelerating) each particle toward its pbest and gbest locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest locations.

PSO is a meta heuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, meta heuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO does not use the derivative of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc.

Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. The updated position and velocity are given by (6.1) – (6.2).

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{6.1}$$

$$V_i^{k+1} = w*V_i^k + c_1*rand_i*(Pbest-X_i^k) + c_2*rand_i*(Pbest-X_i^k) \tag{6.2}$$

where, V_i^{k+1} = velocity of individual i at iteraion k, w = inertia weight parameter (0.5-1).

c_1 and c_2 are weight factors(generally 1), $rand_1$, $rand_2$ and $rand_3$ are random numbers between 0 and 1, X_i^{k+1} = position of individual i at iteraion k, $Pbest_i^k$ = best position of individual i at iteraion k, $Gbest^k$ = best position of group until at iteraion k.

The acceleration constants c_1 and c_2 in equation (6.2) represent the weighting of the stochastic acceleration terms that pull each particle toward pbest and gbest positions. Thus, adjustment of these constants changes the amount of "tension" in the system. Low values allow particles to roam far from target regions before being tugged back, while high values result in abrupt movement toward, or past, target regions. So, a proper value of acceleration constant must be chosen as per the problem.

Particles' velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user, then the velocity on that dimension is limited to Vmax. Vmax is therefore an important parameter. It determines the resolution, or fineness, with which regions between the present position and the target (best so far) position are searched. If Vmax is too high, particles might fly past good solutions. If Vmax is too small, on the other hand, particles may not explore sufficiently beyond locally good regions. In fact, they could become trapped in local optima, unable to move far enough to reach a better position in the problem space. So, a proper value of Vmax is required in order to solve the problem within the limits of error.

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

The choice of PSO parameters can have a large impact on optimization performance. Selecting PSO parameters that yield good performance has therefore been the subject of much research. The PSO parameters can also be tuned by using another overlaying optimizer, a concept known as meta-optimization. Parameters have also been tuned for various optimization scenarios.

6.4.1 Convergence criterion and specifications of Particle Swarm Optimization

The convergence specifications of the algorithm are given in Table - 6.5.

TABLE 6.5 SPECIFICATIONS OF CONVERGENCE FOR PARTICLE SWARM OPTIMIZATION

Parameter	Value
Time limit	Infinite
Maximum no. of iterations	3000
No of particles	28
Function tolerance	10^{-6}
Non linear constraint tolerance	10^{-6}
Inertia Weight 'w'	0.7
Weight factors 'c_1' and 'c_2'	1

6.5 ENERGY OPTIMIZATION USING PARTICLE SWARM OPTIMIZATION

6.5.1 Energy optimization for fixed gradient

Mathematical model of energy consumption as derived from speed-time curve is given by (3.14) - (3.16). The constraints are defined by the equation (5.3) - (5.4). Energy equation is now optimized by genetic algorithm under the above said constraints.

The optimized energy and corresponding parameters are shown in Table - 6.6

TABLE 6.6 OPTIMIZED PARAMETERS OBATAINED FOR FIXED GRADIENT USING PARTICLE SWARM OPTIMIZATION

Gradient → Parameter ↓	Positive	Negative	Zero
Acceleration 'α' (m/s^2)	0.6	0.57	0.49
Acceleration time 't_1' (s)	77.2	78.8	80.4
Free Run Period 't_2' (s)	1853	1915	1963.5
Energy Consumption (kWh)	626	418.3	457.5
No of Iterations	143	112	129

Fig. 6.10 shows the variation of function value for every iteration for positive gradient. It can be observed that the optimum point is achieved after 143^{th} iterations. Fig. 5.11 shows the constraint violation for every iteration for positive gradient.

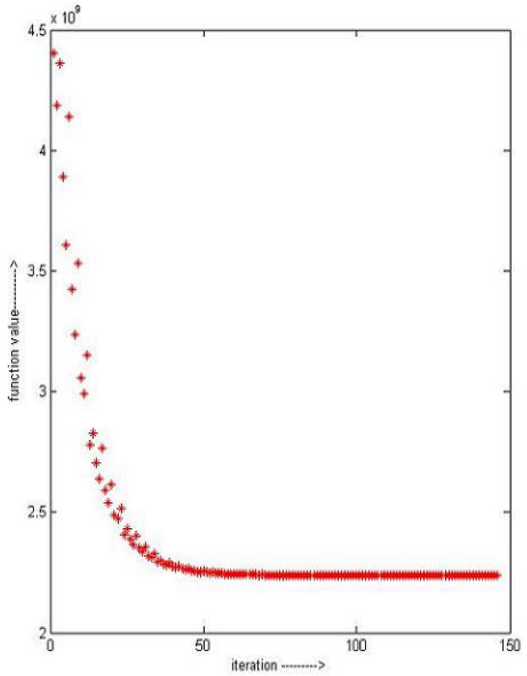

Fig. 6.10 Variation of function value for positive gradient using PSO

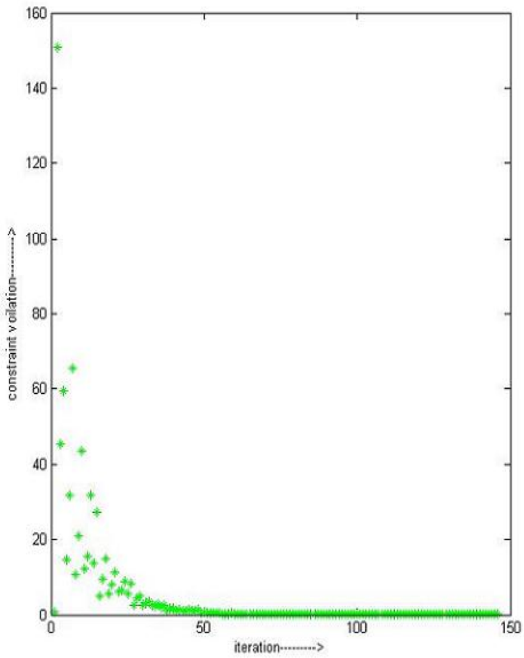

Fig. 6.11 Constraint violation for positive gradient using PSO

Both the above plots are for positive gradient. Similar plots can be drawn for negative and zero gradients.

Fig. 6.12 shows the speed-time trajectory corresponding to optimized parameters for particle swarm optimization.

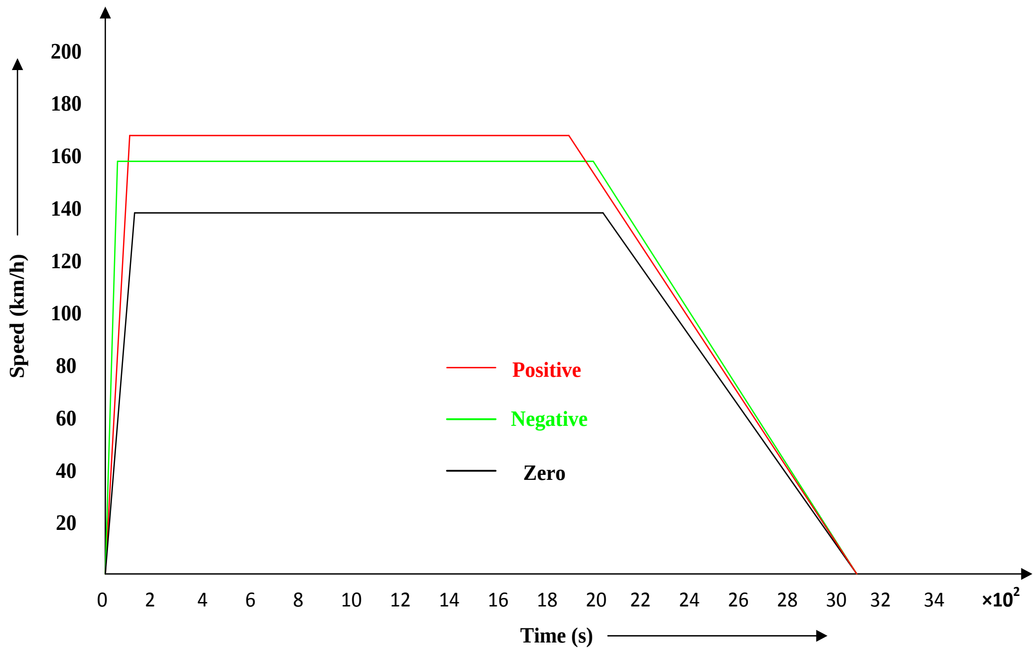

Fig. 6.12 Optimized speed-time trajectory for fixed gradient using PSO

6.5.2 Energy optimization for variable gradient and fixed acceleration

Equation of energy consumption as derived from speed-distance curve is given by (4.8) - (4.14). This equation is optimized under the constraints defined by the speed profile of the section (Table – 4.2). The optimized energy and corresponding parameters are given in Table - 6.7.

TABLE 6.7 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND FIXED ACCELERATION USING PARTICLE SWARM OPTIMIZATION

Parameter	**Value**
a_1 (m/s^2)	0.5
S_1 (m)	562
a_3 (m/s^2)	0.45
S_3 (m)	149
β_5 (m/s^2)	0.20
S_5 (m)	992.4
a_6 (m/s^2)	0.16
S_6 (m)	415.6
β_7 (m/s^2)	0.36
S_7 (m)	327.6
Total energy Consumption (kWh)	22.98
Total Time (min)	7.86

Fig. 6.13 shows the variation of function value for every iteration for sub section -1. Fig. 6.14 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

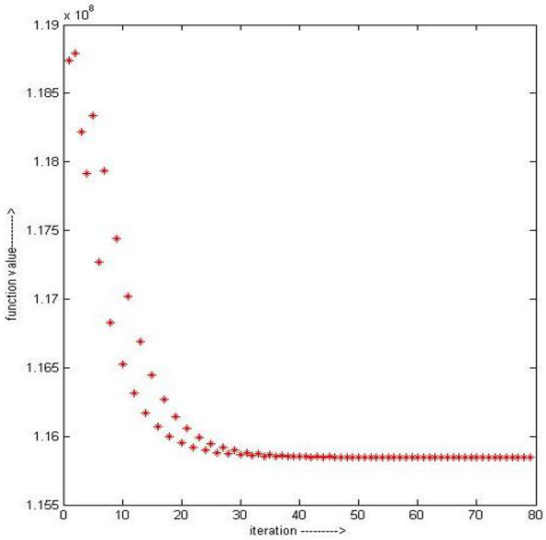

Fig. 6.13 Variation of function value for variable gradient and fixed acceleration using PSO

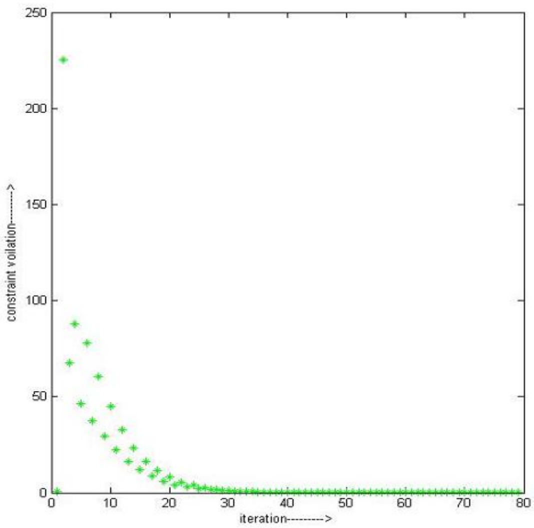

Fig. 6.14 Constraint violation for variable gradient and fixed acceleration using PSO

Fig. 6.15 shows the speed-distance trajectory corresponding to optimized parameters for particle swarm optimization.

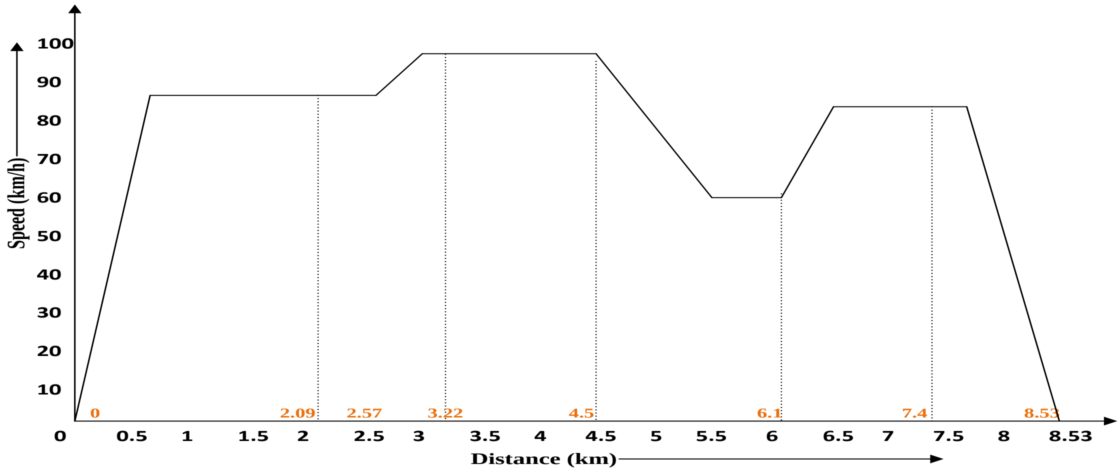

Fig. 6.15 Optimized speed- distance trajectory for variable gradient and fixed acceleration using PSO

6.5.3 Energy optimization for variable gradient and variable acceleration

energy consumption equation as derived from speed-distance curve is given by (4.16) -(4.22). This equation is optimized under the constraints defined by Table - 4.2. The optimized energy and corresponding parameters are given in Table - 6.8.

TABLE 6.8 OPTIMIZED PARAMETERS OBTAINED FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION USING PARTICLE SWARM OPTIMIZATION

Parameter	**Value**
a_{1a} (m/s^2)	0.46
S_{1a} (m)	275.39
a_{1b} (m/s^2)	0.27
S_{1b} (m)	600.7
a_{3a} (m/s^2)	0.27
S_{3a} (m)	186.9
a_{3b} (m/s^2)	0.24
S_{3b} (m)	180
β_{5a} (m/s^2)	0.27
S_{5a} (m)	473.4
β_{5b} (m/s^2)	0.29
S_{5b} (m)	437.1
a_{6a} (m/s^2)	0.31
S_{6a} (m)	255.2
a_{6b} (m/s^2)	0.1
S_{6b} (m)	192
β_{7a} (m/s^2)	0.26
S_{7a} (m)	600
β_{7b} (m/s^2)	0.35
S_{7b} (m)	600
Total energy Consumption (kWh)	22.88
Total Time (min)	7.99

Fig. 6.16 shows the variation of function value for every iteration for sub section -1 and Fig. 6.17 shows the constraint violation for every iteration. These plots are for the section -1. Similar plots can be drawn for the remaining six sections.

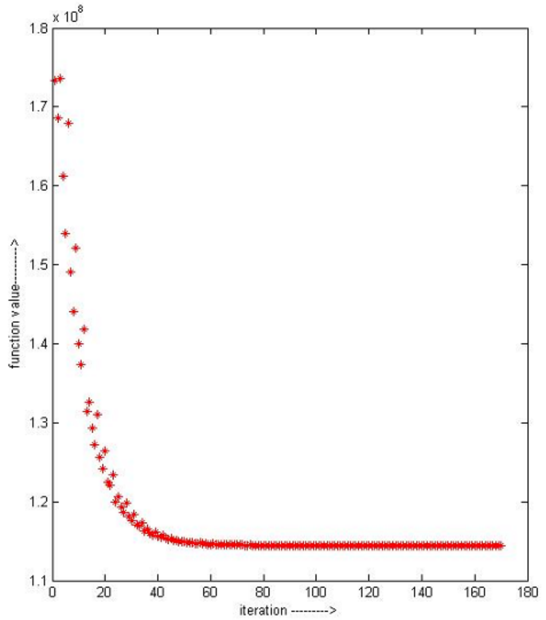

Fig. 6.16 Variation of function value for variable gradient and variable acceleration using PSO

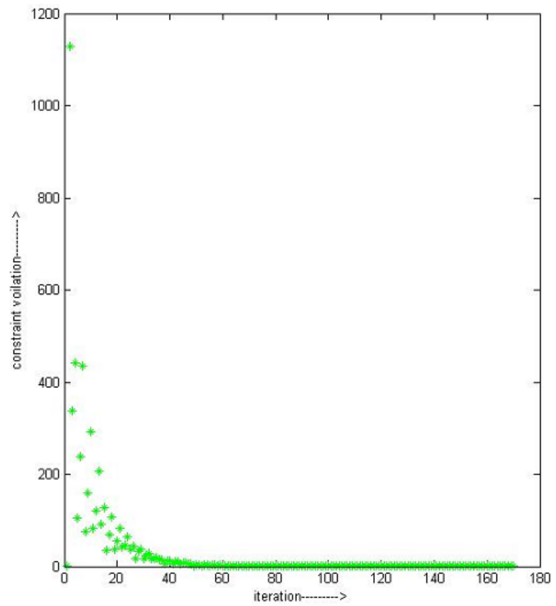

Fig. 6.17 Constraint violation for variable gradient and variable acceleration using PSO

Fig. 6.18 shows the speed-distance trajectory corresponding to optimized parameters for interior point method.

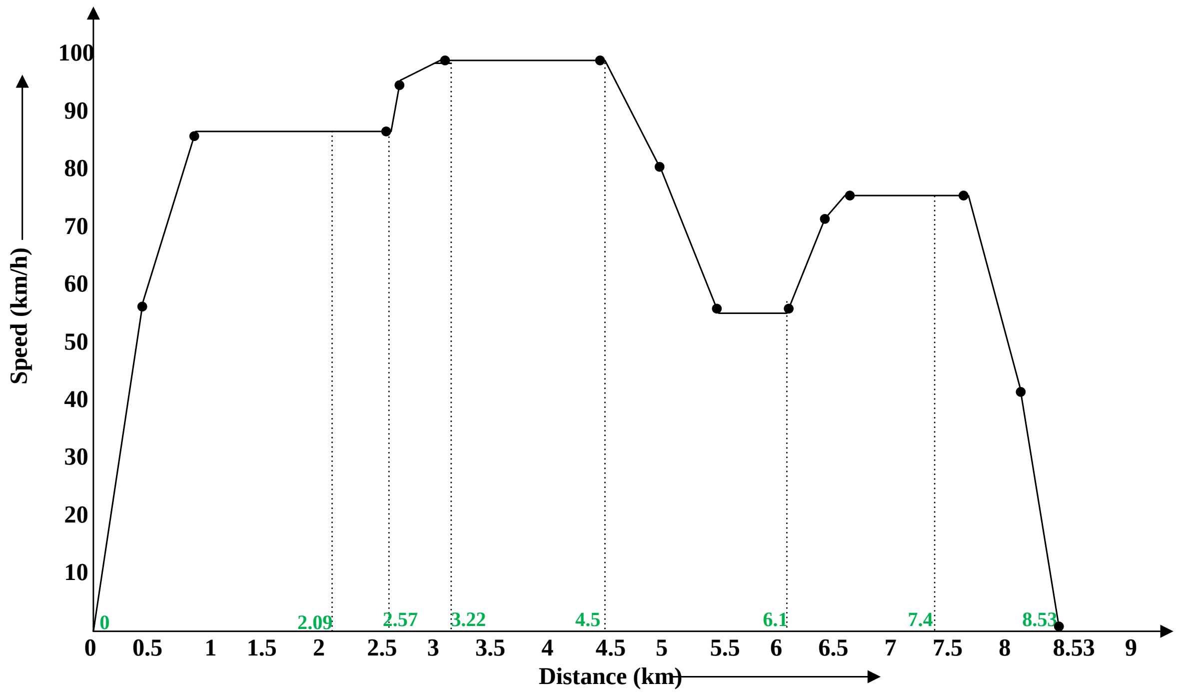

Fig. 6.18 Optimized speed-distance trajectory for variable gradient and variable acceleration using PSO

6.6 CONCLUSION

This chapter presents the various evolutionary and stochastic optimization methods. Optimization of energy consumption derived using both speed-time curve and speed-distance curve has been done using these methods and the graph of function value and constraint violations has been plotted with iteration number. Further, optimized speed-time and speed-distance trajectories are plotted. It has been observed that particle swarm optimization provides better results.

CHAPTER 7
RESULTS & DISCUSSIONS

GENERAL

Optimization of tractive energy derived from speed-time and speed-distance curve has been done using both conventional as well as intelligent optimization methods in the earlier chapters. This chapter gives the comparison of the results obtained earlier in both tabular as well as graphical form.

7.2 COMPARISON OF ENERGY OPTIMIZATION RESULTS OBTAINED FROM SPEED-TIME CURVE FOR FIXED GRADIENT

Tractive energy consumption from speed-time curve has been derived in (3.13) and optimization of the same has been done in the earlier chapters using both conventional as well as intelligent optimization methods. The results obtained from these methods have been compared in Table - 7.1.

TABLE 7.1 COMPARISON OF RESULTS OBTAINED FROM SPEED-TIME CURVE FOR FIXED GRADIENT

Energy Optimization Technique → **Parameters Obtained ↓**	**Gradient ↓**	**Interior Point Method**	**Pattern Search Method**	**Genetic Algorithm**	**Particle Swarm Optimization**
Acceleration 'α' (m/s^2)	Positive	0.2	0.23	0.35	0.6
	Negative	0.3	0.28	0.2	0.57
	Zero	0.1	0.16	0.5	0.49
Acceleration time 't_1' (s)	Positive	200	204.1	110.3	77.2
	Negative	225	60	221.6	78.8
	Zero	359.7	299.8	85.3	80.4
Free run period 't_2' (s)	Positive	2400	2152	2871.3	1853
	Negative	2000	1941	2751.8	1915
	Zero	2600	2457	2481	1963.5
Energy Consumption (kWh)	Positive	680.8	670	667.2	626
	Negative	503.4	491.7	437.4	418.3
	Zero	565.6	564.9	563.8	457.5

It has been observed that PSO provides best results with decrease in energy consumption as compared to Interior Point Method for positive, negative and zero gradients.

Fig. 7.1 shows the speed-time curve corresponding to optimized parameters. This graph is plotted for positive gradient. Similar graphs can be plotted for negative and zero gradients.

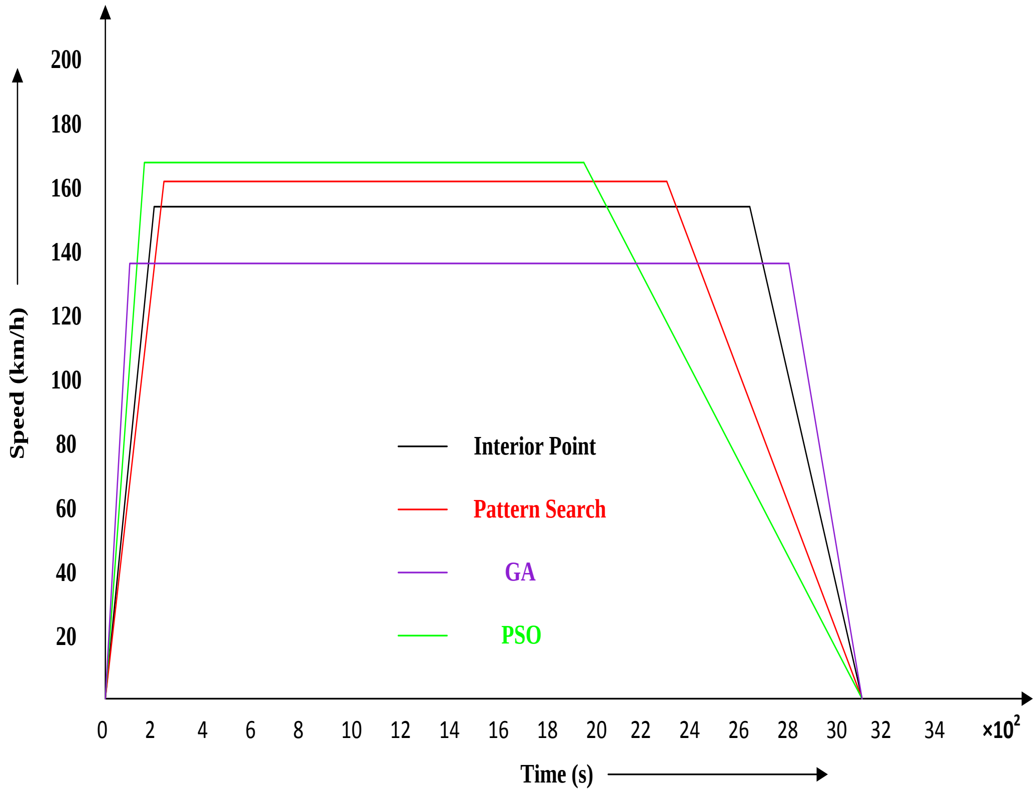

Fig. 7.1 Speed-time curve corresponding to optimized parameters for various optimization methods

It has been observed that V_m is maximum in case of PSO and minimum in case of GA. Further, acceleration is maximum in case of PSO and minimum in case of Interior Point Method.

7.3 COMPARISON OF ENERGY OPTIMIZATION RESULTS OBTAINED FROM SPEED-DISTANCE CURVE FOR VARIABLE GRADIENT AND FIXED ACCELERATION

Tractive energy consumption from speed-distance curve has been derived for variable gradient and fixed acceleration in (4.8) - (4.14). Optimization of the same has been done in the earlier chapters using both conventional as well as intelligent optimization methods. The results obtained from these methods have been compared in Table - 7.2.

TABLE 7.2 COMPARISON OF RESULTS OBTAINED FROM SPEED-DISTANCE CURVE FOR VARIABLE GRADIENT AND FIXED ACCELERATION

Energy Optimization Method → Parameter Obtained ↓	**Interior Point Method**	**Pattern Search Method**	**Genetic Algorithm**	**Particle Swarm Optimization**
a_1 (m/s^2)	0.506	0.505	0.43	0.5
S_1 (m)	551	551	656.4	562
a_3 (m/s^2)	0.335	0.26	0.54	0.45
S_3 (m)	200	250	120	149
β_5 (m/s^2)	0.294	0.294	0.2	0.20
S_5 (m)	700	700	1181.3	992.4
a_6 (m/s^2)	0.175	0.17	0.175	0.16
S_6 (m)	400	400	400	415.6
β_7 (m/s^2)	0.28	0.286	0.25	0.36
S_7 (m)	343	400	320	327.6
Total energy Consumption (kWh)	23.89	23.8	23.7	22.98
Total Time (min)	7.93	7.96	8.03	7.86

It has been observed that PSO provides best results with decrease in energy consumption as well as running time as compared to Interior point method.

Fig. 7.2 shows the speed-distance curve corresponding to optimized parameters for all the above mentioned optimization methods.

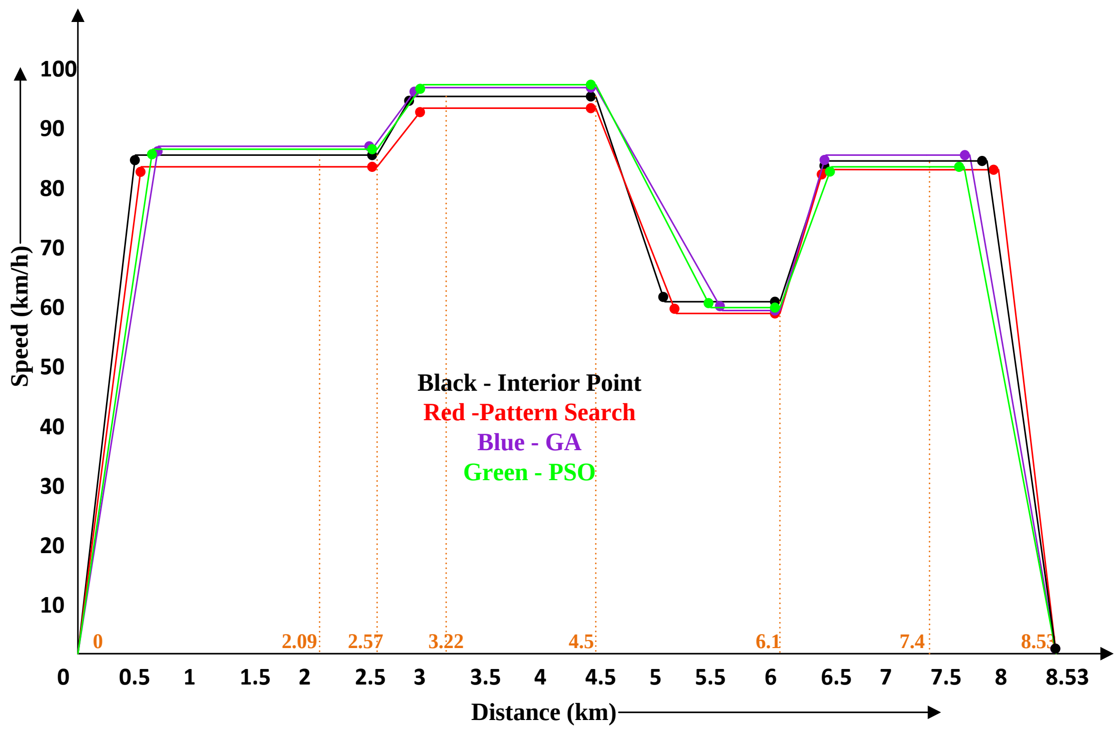

Fig. 7.2 Speed-distance curve corresponding to optimized parameters for variable gradient and fixed acceleration

7.4 COMPARISON OF ENERGY OPTIMIZATION RESULTS OBTAINED FROM SPEED-DISTANCE CURVE FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION

Tractive energy consumption from speed-distance curve has been derived for variable gradient and fixed acceleration in (4.16) - (4.22). Optimization of the same has been done in the earlier chapters using both conventional as well as intelligent optimization methods. The results obtained from these methods have been compared in Table - 7.3.

TABLE 7.3 COMPARISON OF RESULTS OBTAINED FROM SPEED-DISTANCE CURVE FOR VARIABLE GRADIENT AND VARIABLE ACCELERATION

Energy Optimization Method → Parameter Obtained ↓	**Interior Point Method**	**Pattern Search Method**	**Genetic Algorithm**	**Particle Swarm Optimization**
a_{1a} (m/s^2)	0.4	0.35	0.4	0.46
S_{1a} (m)	344.8	344.7	276.7	275.39
a_{1b} (m/s^2)	0.3	0.18	0.3	0.27
S_{1b} (m)	504.4	815.7	530.8	600.7
a_{3a} (m/s^2)	0.22	0.29	0.32	0.27
S_{3a} (m)	318.18	242.2	216.6	186.9
a_{3b} (m/s^2)	0.1507	0.11	0.12	0.24
S_{3b} (m)	165.9	216.3	216.1	180
β_{5a} (m/s^2)	0.3	0.14	018	0.27
S_{5a} (m)	269.1	554.7	441.4	473.4
β_{5b} (m/s^2)	0.55	0.22	0.25	0.29
S_{5b} (m)	299.7	666.1	583.6	437.1
a_{6a} (m/s^2)	0.3	0.3	0.3	0.31
S_{6a} (m)	213.33	213.33	227.4	255.2
a_{6b} (m/s^2)	0.16	0.2	0.19	0.1
S_{6b} (m)	193.3	160	166.2	192
β_{7a} (m/s^2)	0.21	0.19	0.21	0.26
S_{7a} (m)	188.1	93.65	193.4	600
β_{7b} (m/s^2)	0.34	0.35	0.38	0.35
S_{7b} (m)	688.14	783.6	707.2	600
Total energy Consumption (kWh)	23.4	23.27	23.02	22.88
Total Time (min)	8.2	8.6	8.35	7.99

It has been observed that PSO provides best results with decrease in energy consumption as well as running time as compared to Interior point method.

Fig. 7.3 shows the speed-distance curve corresponding to optimized parameters for all the above mentioned optimization methods.

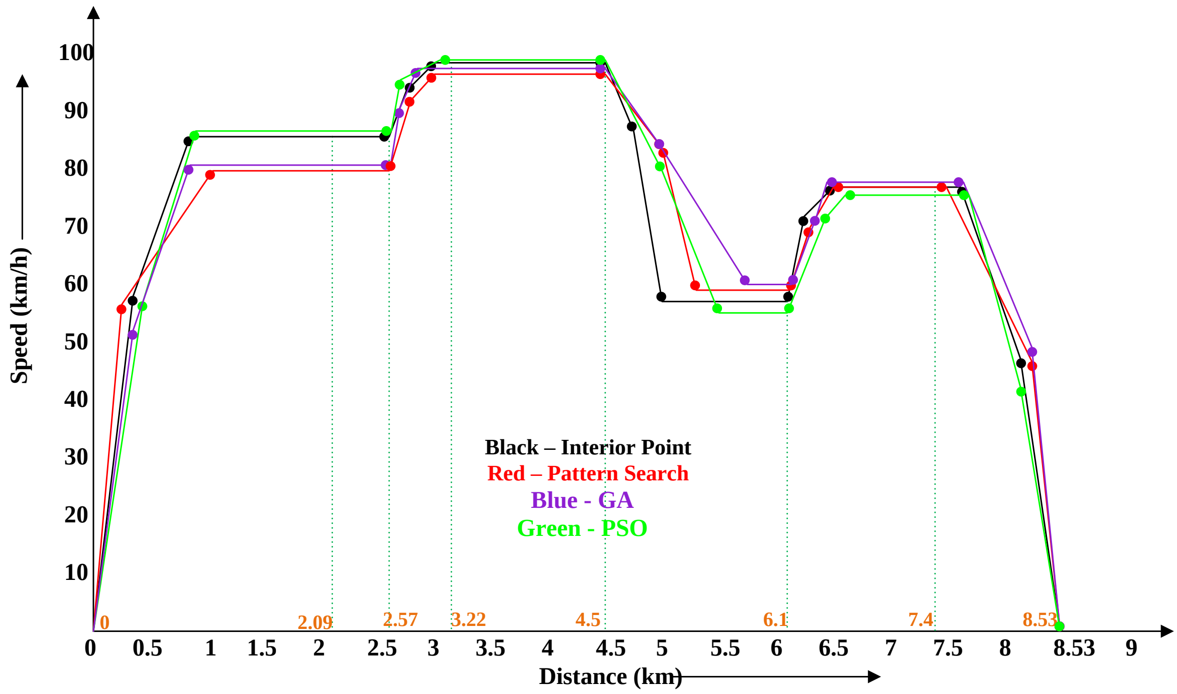

Fig. 7.3 Speed-distance curve corresponding to optimized parameters for variable gradient and variable acceleration

7.5 CONCLUSION

In this chapter, various conventional as well as intelligent optimization methods has been compared with respect to parameters obtained from energy consumption equations derived from speed-time as well as speed-distance curves. It has been observed that PSO provides best results among all the methods.

CHAPTER 8
CONCLUSION AND FUTURE SCOPE OF WORK

8.1 CONCLUSION

In this dissertation first of all, the power flow model of modern electric traction system has been presented describing the tractive as well as non-tractive energy consumption. Tractive effort required for train propulsion has been studied and mathematical model of tractive energy consumption using speed-time curve for fixed gradient has been developed. Sensitivity analysis of the derived tractive energy consumption with respect to parameter of interest has been carried out. It has been observed that energy consumption is most sensitive with respect to maximum velocity and least sensitive with respect to free running period.

Further, it has been observed that tractive energy consumption studies are not suitable using speed-time curve when gradient is variable. So, tractive energy consumption model using speed-distance curve has been developed for variable gradient. Further, tractive energy consumption model has been developed for variable gradient and variable acceleration.

Also, various conventional (Interior Point and Pattern Search) as well as intelligent (Genetic Algorithm and Particle Swarm Optimization) optimization methods have been studied in detail and optimized tractive energy consumption and corresponding parameters of interest has been obtained using these optimization methods. A detailed comparison of results obtained from the various optimization methods has been done. It has been observed that Particle Swarm Optimization provides best results as compared to all other methods. These studies are helpful for designers while designing the system.

8.2 FUTURE SCOPE OF WORK

There are several points which may further be investigated but couldn't be covered in this work due to limited time frame. The main points are described below.

1) The thesis work carried out here is useful for calculating the parameters corresponding to optimized tractive energy consumption for sub-urban railways like DMRC. If real time data of Delhi Metro can be acquired then these studies will be very helpful there.

2) The studies done in this work are based upon approximate speed-time and speed-distance curves. If more accurate equations can be formulated by collecting the sufficient real time data, it would then lead to more accurate analysis.

REFERENCES

[1] A.F. Anderson, "Unusual electric machines", *IET journals & Magazines on Electronics and Power*, vol. 20, pp. 979-983, Aug. 2009.

[2] G.D. Friedlander and S. Writer, "Railroad electrification: past, present and future development of great European systems", *IEEE Spectrum*, pp. 77-90, Sept. 1968.

[3] G.D. Friedlander and S. Writer, "Railroad electrification: past, present and future history of systems in the United States", *IEEE Spectrum*, pp. 50-65, July, 1968.

[4] M.C. Duffy, " Three-phase motor in railway traction", *IEE Proceedings on Science, Measurement and Technology*, pp. 329-337, Nov. 1992.

[5] J. Wang, L. Xue, Y. Liu and M. Li, "The interaction research between public grid and traction power supply system", *Int. Conf. on electricity distribution*, Guangzhou, China, pp. 1-8, Dec. 2008.

[6] C.J. Goodman, "Overview of electric railway systems and the calculation of train performance", IET *professional development course on Electric traction systems*, London, pp. 1-24, Nov. 2010.

[7] T. H. Chen, "Simplified models of electric railway substations for three phase power flow studies", *IEEE annual meeting on industry application*, Denver, CO, vol.3, pp. 2245-2248, Oct. 1994.

[8] D. Gonzalez and F. Manzanedo, "Power loss minimization in DC electric railways by means of traction substations coordinated voltage control", *IET Conf. on railway traction systems*, Birmingham, pp. 1-5, Apr. 2010.

[9] C. R. Akli, X. Roboam, B. Sareni and A. Jeunesse, "Energy management and sizing of a hybrid locomotive", *European Conf. on power electronics and applications*, Aalborg, pp. 1-10, Sept. 2007.

[10] W. J. A. Sykes, "Electric locomotives of the British Railways" *IEE proceedings on Electric railway traction*, pp. 178-187, 1950.

[11] H. Stemmler, "power electronics in electric traction applications", *Int. Conf. on Industrial Electronics, Control and Instrumentation*, Maui, HI, vol. 2, pp. 707-713, Nov. 1993.

[12] E. Ohno and M. Akamatsu, "High-voltage multiple phase thyristor chopper for traction motor control, *IEEE Trans. on magnetic*, pp. 232-236, Sept. 1967.

[13] Z. S. Mouneimne and B. Mellitt, "Modelling of inverter-controlled asynchronous drives for system simulation in DC railways*", IEE proceedings Electric power applications,* pp. 210-217, Sept. 1988.

[14] M. M. Bakran, H. G. Eckel, P. Eckert and H. Gambach, "Comparison of multisystem traction converters for high power locomotives", *IEEE 35th annual Conf. of power electronics specialist*, vol.1, pp. 697-703, June 2004.

[15] Z. Zhang, B. Wu, L. Luo and L. Zhou, "Multi-purpose balanced transformer with harmonic eliminating capability for railway traction applications", *IEEE general meeting on Conversion and delivery of electrical energy in the 21st century,* Pittsburgh, PA, pp. 1-8, July 2008.

[16] R. W. Schreyer, D. A. Dreisbach and A. Ducourret, "IGBT based propulsion improving vehicle reliability and availability", *proceedings of ASME/IEEE joint Railroad Conf,* Oakbrook, IL, pp. 41-58, May 1996.

[17] R. Y. Faddoul and S. R. Stone, " Auxiliary inverters for traction", *IEEE Colloquium on GTO's rival devices and applications,* London, pp. 4/1-4/9, Mar. 1988.

[18] C. H. Bae, D. Jang, Y. Kim and S. Chang, "Calculation of regenerative energy in DC 1500V electric railway substations", *IEEE 7th Int. Conf. on power electronics,* Daegu, pp. 801-805, Oct. 2007.

[19] F. Whyman, "Railway electric braking systems", *IEE proceedings on Electric railway traction,* pp. 276-283, 1950.

[20] E. Agenjos, F. G. Franco and R. Molina, "Energy efficiency in railways: Energy storage and electric generation in diesel electric locomotives*", IET 20th Int. Conf. on Electricity distribution,* Prague, Czech Republic, pp. 1-7, June 2009.

[21] J. M. W. Whiting, "A regenerative braking system for d.c. railway traction" *IET conf. on electronics and power,* pp. 710-714, Oct. 1979.

[22] X. Chen, D. Liang and W. Zhang, "Braking energy recovery for electric traction based on super-capacitor and bidirectional DC-DC converter", *IEEE Int. Conf. on power electronics and motion control,* Harbin, China, pp. 879-883, June 2012.

[23] T. Koseki, Y. Hamazaki and K. Kondo, "Technology for energy-saving railway operation through power-limiting brakes- A case study at an urban railway", *IEEE Int. Conf. on power electronics,* Hiroshima, pp. 2126-2132, May 2014.

[24] K. Tseng and Y. Shiao, "The analysis of regenerative braking power for Taipei Rapid Transit Systems Electrical Multiple Units", *IEEE Int. Conf. on machine learning and cybernetics,* Xian, pp. 1947-1951, July 2012.

[25] J. Lee, H. Lee and J. Kwak, "A study for improvement performance of electric brake for electric train", *IEEE Int. Conf. on Control, Automation and Systems,* Seoul, pp. 1345-1348, Oct. 2008.

[26] Q. Wang, J. Gao, K. Chen and X. Gao, "Reliability sensitivity analysis based on system failure evolution", *IEEE Annual Symposium on Reliability and maintainability,* Palm Harbor, FL, pp. 1-6, Jan. 2015.

[27] Q. Hua, R. Zheng, S. Lei and Z. Bo, "A new life cycle cost model of power transformer and its comprehensive sensitivity analysis", *IEEE Int. Conf. on power system technology*, Chengdu, pp. 1342-1348, Oct. 2014.

[28] L. Lai and M. Ehsani, "Sensitivity analysis of vehicle performance to transmission parameters in parallel HEVs with dynamic programming optimization", *IEEE Int. Conf. on Transportation Electrification,* Dearborn, MI, pp. 1-5, June 2012.

[29] J. Mao, J. Wang and E. Kuh, "Simulation and sensitivity analysis of transmission line circuits by the characteristics method", *IEEE/ACM int. Conf. on Computer-Aided Design,* San Jose, USA, pp. 556-562, Nov. 1996.

[30] P. Mahajan, R. Garg and P. Kumar, "Sensitivity analysis of railway electric traction system," *IEEE International Conference on Power Electronics (IICPE),* New Delhi, pp. 1-5, Jan 2011.

[31] K. Bennion and J. Cousineau, "Sensitivity analysis of traction drive motor cooling", *IEEE Int. Conf. on Transportation Electrification,* Dearborn, MI, pp. 1-6, June 2012.

[32] S. Gupta, P. Mahajan and R. Garg, "Sensitivity model of energy consumption by railway electric locomotive", *Annual IEEE India Conference, New Delhi, pp. 1-5,* 17-20 Dec. 2015.

[33] S. Danielsen, O. Fosso and T. Toftevaag, "Use of participation factors and parameter sensitivities in study and improvement of low frequency stability between electrical rail vehicle and power supply", *IEEE European Conf. on power electronics and applications,* Barcelona, pp. 1-10, Sept. 2009.

[34] P. Mahajan, R. Garg and P. Kumar, "Sensitivity analysis of pantograph-catenary system model," *IEEE International Conference on Power Electronics (IICPE),* Delhi, pp. 1-4, Dec 2012.

[35] S. Jabbehdari and A. Maricotti, "Sensitivity analysis of multilayer earth model", *IEEE Conf. on Electric systems for Aircraft, Railway and Ship Propulsion,* Bologna, pp. 1-6, Oct. 2012.

[36] M. Brenna and F. Foiadelli, “Sensitivity analysis of the Constructive Parameters for the 2×25-kV High-Speed Railway Lines Planning”, *IEEE Transactions on Power delivery*, pp. 1923-1931, Apr. 2010.
[37] H. Li, L. Lee and E. P. Chew, “Optimization via gradient oriented polar random search”, *Proceedings of IEEE Winter Simulation Conf.* Berlin, pp. 1-12, Dec. 2012.
[38] Z. Tang, “Adaptive partitioned random search to global optimization”, *IEEE Transactions on Automatic Control,* vol. 39, pp. 2235-2244, Nov. 1994.
[39] C. Zhu, J. Xu, C. Chen and L. Lee, “Balancing search and estimation in random search based stochastic simulation optimization”, *IEEE Transactions on Automatic control,* vol.1, pp. 1, Jan. 2016.
[40] G. D. Irisarri, X. Wang, J. Tong and S. Mokhtari, “maximum loadability of power systems using interior point nonlinear optimization method”, *IEEE transactions on power systems,* vol. 12, pp. 162-172, Feb. 1997.
[41] Z. Fan, X. Chang and h. Wang, “Discrete reactive power optimization based on interior point filter algorithm and complementarity theory”, *IEEE Int. Conf. on Power System Technology,* Chengdu, pp. 210-214, Oct. 2014.
[42] M. Dorigo, M. Birattari and T. Stutzle, “Ant colony optimization”, *IEEE Computational Intelligence Magazine*, vol.1, issue: 4, pp. 28-39, Nov. 2006.
[43] M. K. Vai, S. Prasad, N. C. Li and F. Kai, “modelling of microwave semiconductor devices using simulated annealing optimization”, *IEEE Transactions on Electron Devices,* vol. 36, pp. 761-762, Apr. 1989.
[44] J. F. Frenzel, “Genetic algorithms”, *IEEE Potentials*, vol.12, issue:3, pp. 21-24, ISSN:0278-6648, DOI 10.1109/45.282292, Oct 1993.
[45] Y. Dong, J. Gu, N. Li and X. Hou, “Combination of Genetic Algorithm and Ant Colony Algorithm for Distribution Network Planning”, *IEEE Int. Conf. on Machine Learning and cybernetics,* Hong Kong, vol. 2, pp. 999-1002, Aug. 2007.
[46] P. Guo, X. Wang and Y. Han, “The enhanced genetic algorithms for the optimization design”, *IEEE Int. Conf. on biomedical engineering and informatics,* Yantai, pp. 2990-2994, Oct. 2010.
[47] J. Kennedy and R. Eberhart, “Particle swarm optimization”, *IEEE int. Conf on neural networks,* Perth, WA, vol. 4, pp. 1942-1948, Nov/Dec. 1995.
[48] X. Hu, L. Wang and Y. Zhong, “An improved particle swarm optimization algorithm for site index curve model”, *IEEE Int. Conf. on business management and electronic information,* Guangzhou, pp. 838-842, May 2011.

[49] Y. V. Bocharnikov, A.M. Tobias, C. Roberts, S Hillmansen and C J. Gordon, " Optimal Driving strategy for traction energy saving on DC suburban railways", *IET Electric Power Applications,* pp. 672-682, Aug. 2007.

[50] Y. Fan, B. Cai, W. Shangguan, J. Wang and D. Jiang, " Multi-objective operation control of rail vehicles", *International symposium on Intelligent Vehicles(IV),* Gold Coast, QLD, pp. 1265-1270, June 2013.

[51] Richard A. Uher, N. Sathi and A. Sathi, "Traction Energy cost reduction of the WMATA metro rail system", *IEEE Transaction on Industry Applications,* vol. IA- 20, pp. 472-483, May 1984.

[52] Y. V. Bocharnikov, A.M. Tobias and C. Roberts, "Reduction of train and net energy consumption using genetic algorithms for trajectory optimization." *IEEE conf. on railway traction systems (RTS 2010),* Birmingham, vol. 1, pp. 1-5, April 2010.

[53] T. Moritani, and K. Kondo, "Basic study on a designing method of the traction equipments to save the running energy with an optimization method", *International Conference on Electrical systems for aircrafts, railway and ship propulsion(ESARS),* Bologna, pp. 1-6, Oct. 2010.

[54] G. Acampora, C. Landi, M. Luiso and N. Pasquino, "Optimization of energy consumption in railway traction system*", International symposium on power electronics, electric drives automation and motion,* Speedam , pp. 1121-1126, May 2006.

[55] D. Grillo, C. Landi, M. Luiso and N. Pasquino, " An on-board monitoring system for electrical railway traction systems", *Proceedings of IEEE International Conference on Instrumentation and measurement Technology,* Sorrento, pp. 2306-2311, April 2006.

[56] Z. Tian, S. Hillmansen, C. Roberts and P. Weston, "Modelling and simulation of DC rail traction systems for energy saving", *Int. Conf. on intelligent transportation systems (ITSC),* Qingado, pp. 2354-2359, Oct. 2014.

[57] Y. Song and W. Song, "A novel dual speed-curve optimization based approach for energy-saving operation of high-speed trains", *IEEE Transactions on Intelligent Transportation Systems,* pp. 1-12, Jan 2016.

[58] S. Lu, S. Hillmansen, T. Ho and C. Roberts, "Single-Train Trajectory Optimization", *IEEE Transactions on Intelligent Transportation Systems,* vol.14, pp. 743-750 ,June 2013.

[59] S Hillmansen, " Electric railway traction systems and techniques for energy saving", *IET Professional Development course on Electric Traction Systems,* London, UK, pp. 19-23, Nov 2012.

LIST OF PUBLICATIONS

[1] S. Gupta, P. Mahajan and R. Garg, “Sensitivity model of energy consumption by railway electric locomotive”, *Annual IEEE India Conference, INDICON-2015, New Delhi, pp. 1-5,* DOI: 10.1109/INDICON.2015.7443489.

[2] S. Gupta, P. Mahajan and R. Garg, “Tractive energy optimization in railway electric traction system”, accepted in IEEE 1st Internatinal Conference on Power Electronis, Intelligent control and Energy Systems, ICPEICES-2016, Delhi, to be published on IEEE Explore.