NON-WEIGHTED AGGREGATE EVALUATION FUNCTION OF MULTI-OBJECTIVE OPTIMIZATION FOR KNOCK ENGINE MODELING

AZHER RAZZAQ HADI WITWIT

DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2017

Awang Had Salleh
Graduate School
of Arts And Sciences

Universiti Utara Malaysia

PERAKUAN KERJA TESIS / DISERTASI
(Certification of thesis / dissertation)

Kami, yang bertandatangan, memperakukan bahawa
(We, the undersigned, certify that)

AZHER RAZZAQ HADI WITWIT

calon untuk Ijazah PhD
(candidate for the degree of)

telah mengemukakan tesis / disertasi yang bertajuk:
(has presented his/her thesis / dissertation of the following title):

"NON-WEIGHTED AGGREGATE EVALUATION FUNCTION OF MULTI-OBJECTIVE OPTIMIZATION FOR KNOCK ENGINE MODELING"

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.
(as it appears on the title page and front cover of the thesis / dissertation).

Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan, sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada : *17 November 2015.*
That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on: November 17, 2015.

Pengerusi Viva: *(Chairman for VIVA)*	Prof. Dr. Che Su Mustaffa	Tandatangan *(Signature)*
Pemeriksa Luar: *(External Examiner)*	Prof. Dr. Siti Mariyam Hj Shamsuddin	Tandatangan *(Signature)*
Pemeriksa Dalam: *(Internal Examiner)*	Prof. Dr. Ku Ruhana Ku Mahamud	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	Assoc. Prof. Dr. Azman Yasin	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	Prof. Dr. Horizon Walker Gitano-Briggs	Tandatangan *(Signature)*

Tarikh:
(Date) November 17, 2015

Permission to Use

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to:

Dean of Awang Had Salleh Graduate School of Arts and Sciences
UUM College of Arts and Sciences
Universiti Utara Malaysia
06010 UUM Sintok

Abstrak

Dalam teori keputusan, Model Jumlah Wajaran (WSM) adalah kaedah terbaik dalam Analisa Keputusan Multi-Kriteria (MCDA) untuk menilai beberapa alternatif dari segi bilangan keputusan kriteria. Penetapan wajaran merupakan tugas yang sukar, terutama jika bilangan kriteria adalah besar dan kriteria tersebut mempunyai ciri yang berbeza. Terdapat beberapa masalah dalam dunia sebenar yang menggunakan kriteria yang bercanggah dan kesan bersama. Dalam bidang automotif, fenomena ketukan dalam enjin pembakaran atau pencucuhan bunga api dalaman menghadkan kecekapan enjin. Kuasa dan ekonomi bahan api boleh dimaksimumkan dengan mengoptimumkan beberapa faktor yang mempengaruhi fenomena ketukan, seperti suhu, sensor kedudukan pendikit, masa pencucuhan bunga api, dan revolusi per minit. Mengesan ketukan dan mengawal factor atau kriteria di atas membolehkan enjin berjalan pada kuasa dan bahan api terbaik ekonomi. Keputusan terbaik mesti diambil daripada trade-off yang paling optimum dalam pemilihan kriteria tersebut. Objektif utama kajian ini adalah untuk mencadangkan satu model baharu Fungsi Penilaian Aggregat Bukan-Wajaran (NWAEF) untuk bukan linear fungsi multi-objektif yang akan meniru tingkah laku ketukan enjin (pembolehubah bersandar bukan linear) untuk mengoptimumkan keputusan faktor bukan linear (pembolehubah bebas bukan linear). Kajian ini telah memberi tumpuan kepada pembinaan satu model NWAEF dengan menggunakan keluk teknik pemasangan dan derivatif separa. Ia juga bertujuan untuk mengoptimumkan sifat bukan linear satu faktor dengan menggunakan Algoritma Genetik (GA) dan juga menyiasat tingkah laku fungsi tersebut. Kajian ini mengandaikan bahawa pengaruh separa dan bersama antara faktor diperlukan sebelum faktor boleh dioptimumkan. The Kriteria Maklumat Akaike (AIC) digunakan untuk mengimbangi kerumitan model dan kehilangan data, yang boleh membantu menilai pelbagai model yang diuji dan memilih yang terbaik. Beberapa kaedah statistik juga digunakan dalam kajian ini untuk menilai dan mengenal pasti penjelasan yang lebih baik dalam model. Terbitan pertama digunakan untuk memudahkan bentuk fungsi penilaian. Model NWAEF telah dibandingkan dengan Genetik Algorithm Wajaran Rawak (RWGA) dengan menggunakan lima set data yang diambil daripada enjin pembakaran dalaman yang berbeza. Terdapat variasi yang agak besar di masa berlalu untuk mendapatkan penyelesaian terbaik antara kedua-dua model. Keputusan pengujian dalam keadaan sebenar (enjin pembakaran dalaman) menunjukkan bahawa model baharu mengambil bahagian dalam mengurangkan masa yang berlalu. Kajian ini merupakan bentuk kawalan ketukan dalam subruang yang boleh meningkatkan kecekapan dan prestasi enjin, meningkatkan ekonomi bahan api dan mengurangkan pelepasan terkawal dan pencemaran. Digabungkan dengan konsep baru dalam reka bentuk enjin, model ini boleh digunakan untuk meningkatkan strategi kawalan dan menyediakan maklumat yang tepat kepada Unit Kawalan Enjin (ECU), yang akan mengawal ketukan pantas dan memastikan keadaan engine yang sempurna.

Kata kunci: Model Jumlah Wajaran, Analisa Keputusan Multi-Criteria, Alogritma Genetik, Kriteria Maklumat Akaike, Keluk Pemasangan

Abstract

In decision theory, the weighted sum model (WSM) is the best known Multi-Criteria Decision Analysis (MCDA) approach for evaluating a number of alternatives in terms of a number of decision criteria. Assigning weights is a difficult task, especially if the number of criteria is large and the criteria are very different in character. There are some problems in the real world which utilize conflicting criteria and mutual effect. In the field of automotive, the knocking phenomenon in internal combustion or spark ignition engines limits the efficiency of the engine. Power and fuel economy can be maximized by optimizing some factors that affect the knocking phenomenon, such as temperature, throttle position sensor, spark ignition timing, and revolution per minute. Detecting knocks and controlling the above factors or criteria may allow the engine to run at the best power and fuel economy. The best decision must arise from selecting the optimum trade-off within the above criteria. The main objective of this study was to proposed a new Non-Weighted Aggregate Evaluation Function (NWAEF) model for non-linear multi-objectives function which will simulate the engine knock behavior (non-linear dependent variable) in order to optimize non-linear decision factors (non-linear independent variables). This study has focused on the construction of a NWAEF model by using a curve fitting technique and partial derivatives. It also aims to optimize the non-linear nature of the factors by using Genetic Algorithm (GA) as well as investigate the behavior of such function. This study assumes that a partial and mutual influence between factors is required before such factors can be optimized. The Akaike Information Criterion (AIC) is used to balance the complexity of the model and the data loss, which can help assess the range of the tested models and choose the best ones. Some statistical tools are also used in this thesis to assess and identify the most powerful explanation in the model. The first derivative is used to simplify the form of evaluation function. The NWAEF model was compared to Random Weights Genetic Algorithm (RWGA) model by using five data sets taken from different internal combustion engines. There was a relatively large variation in elapsed time to get to the best solution between the two models. Experimental results in application aspect (Internal combustion engines) show that the new model participates in decreasing the elapsed time. This research provides a form of knock control within the subspace that can enhance the efficiency and performance of the engine, improve fuel economy, and reduce regulated emissions and pollution. Combined with new concepts in the engine design, this model can be used for improving the control strategies and providing accurate information to the Engine Control Unit (ECU), which will control the knock faster and ensure the perfect condition of the engine.

Keywords: Weighted Sum Model, Multi-Criteria Decision Analysis, Genetic Algorithms, Akaike Information Criterion, Curve Fitting

Acknowledgement

First of all I have to express my thanks and gratitude to Allah who gives me the ability to achieve this imperfect work and without his blessing and support nothing can be done.

It gives me great pleasure to express my gratefulness to everyone who contributed in completing this thesis. It was my pleasure to study under Associate Professor Dr. Azman Yasin’s supervision. I'm so grateful for his support during the Years period of the study.

I would like to thank my co-supervisor Professor Dr. Horizon Gitano for his advanced ideas and his noble mind. His continuous advice and important comments helped improve my work successfully.

To my father, whose surname I proudly carry – I am forever appreciative. I hope he is proud of me even if he is no longer with us. To my mother, who gave me life and prayed for me all the time, may Allah continuously bless her with good health. To my brother, thanks for their love and support. To my wife Bayadir, who gave her time and patience during the years of study, I thank her from the deeps of my heart. I would also like to thank my two young babies Mustafa and Fatima, without whom my goal would not have been achieved. I dedicate this work to my family.

I thank all the workers in the UUM my university and school of computing to offer all support and facilities to complete this simple work.

Table of Contents

Permission to Use i
Abstrak ii
Abstract iii
Acknowledgement iv
Table of Contents v
List of Tables ix
List of Figures xi
List of Appendices xiii
List of Abbreviations xiv
CHAPTER ONE INTRODUCTION 1
1.1 Background 1
1.2 Problem Statement 6
1.3 Research Questions 9
1.4 Research Objectives 9
1.5 Motivation and Significance of the Research 10
1.6 Scope, Assumption, and Limitations of the Research 12
1.7 Thesis Organization 13
CHAPTER TWO LITERATURE REVIEW 15
2.1 Introduction 15
2.2 Basic concepts of Optimization 15
2.3 Scope of optimization problems 16
2.4 Optimization Problems 17
2.4.1 Solution Process in optimization 17
2.4.2 Properties of Optimization Problems 21
2.4.3 Reviewing of Optimization Methods 22
2.5 Multi-Objective optimization 28
2.5.1 Basic Concept of Multi-Objective Optimization Problems 29
2.5.2 Reviewing Evolutionary Multi-Objective Optimization Approaches 31
2.5.3 Review in Multi-Objective Genetic Algorithm 36
2.6 Aggregating Multi-Objective Optimization 40

2.6.1 Basic Concept of Aggregating Multi-Objective Optimization 41
2.6.2 Related Past Work on Aggregating Multi-Objective Optimization 43
2.7 Past work in Nonlinear Knock Factor Optimization and Evaluation Function 50
2.8 Discussion and Summary 54
CHAPTER THREE RESEARCH METHODOLOGY 56
3.1 Introduction 56
3.2 Phase One: Data Gathering 57
3.3 Phase Two: Objectives Modeling 59
3.3.1 System Identification 62
3.3.2 Aggregation Evaluation Function Methodology 68
3.3.3 Differential calculus and derivatives 69
3.3.4 Partial Derivatives 69
3.4 Phase Three: Optimization Methodology 74
3.4.1 GA in MOOPs 74
3.5 Summary and discussion 78
CHAPTER FOUR CONSTRUCTION AND OPTIMIZATION OF NON-WEIGHTED AGGREGATE EVALUATION FUNCTION 79
4.1 Introduction 79
4.2 Data Selection and Reading 79
4.3 Construct Individual Objectives and Aggregate Multi-objective Evaluation 83
Function 83
4.3.1 Curve Fitting Technique 84
4.3.2 Curve Fitting Methods 84
4.3.3 Akaike Information Criterion 90
4.3.4 Information Loss Estimation by Akaike Information Criterion 90
4.3.5 Goodness of Fit of a Model 92
4.3.6 Residuals 92
4.3.7 Estimation of Regression Model 94
4.3.8 Comparison between (Sinusoidal and Gaussian model) in TPS objective 95
4.4 Objectives Aggregation 98

4.5 Multi-Objectives Optimization using continuous Genetic Algorithm........................ 102
4.5.1 Initial Population.. 103
4.5.2 Natural Selection... 104
4.5.3 Pairing Approaches... 106
4.5.4 Mating.. 110
4.5.5 Mutation... 113
4.6 Model Validation.. 115
4.7 Summary and Discussion 117
CHAPTER FIVE EXPERIMENTAL RESULTS AND ANALYSIS 118
5.1 Introduction 118
5.2 Sample Size Testing 119
5.3 Selecting Factors and its Analysis, Results 120
5.3.1 General Regression Model Analysis: KNOCK versus TPS;TEMP;IGN;RPM 121
5.3.2 General Regression Model Analysis: KNOCK versus TPS; TEMP; RPM 124
5.3.3 General Regression Model Analysis: KNOCK versus TPS; TEMP; IGN........ 127
5.4 Results and analysis of constructing objective functions 132
5.4.1 TPS Objective Results 133
5.4.2 RPM Objective Results.. 140
5.4.3 Temperature Objective Results.. 143
5.4.4 TPS Effect on Knocking 149
5.4.5 RPM Effect on Knocking... 151
5.4.6 TEMP Effect on Knocking 152
5.5 Evaluation.. 164
5.6 Evaluation and Total Error Results 165
5.7 Locality of the problem 169
5.8 Accuracy Results of Optimization... 172
5.9 Summary and Discussion 176
CHAPTER SIX CONCLUSION AND PERSPECTIVES... 178
6.1 Introduction 178
6.2 General Discussion... 179

6.3 Ability of GA to Solve MOOPs 180
6.4 Knock Detection Methods Discussion 181
6.5 Research achievement 182
6.6 Contribution of the Research 184
6.7 Limitations 185
6.8 Recommendations for Future work 185
6.9 Conclusion 186
REFRENCES 188

List of Tables

Table 2.1	Optimization methods……………………………........................	24
Table 3.1	Rules of differentiation……………………………………………	71
Table 4.1	Different test Engines and Conditions …………………………...	83
Table 4.2	Value of A as we vary b……………………………………...........	92
Table 4.3	Overview (Sinusoidal & Gaussian model) in TPS objective...........	97
Table 4.4	Initial Population of 10 Random Chromosomes (N_{pop}=10) and Their Corresponding Cost……………………………………...	108
Table 4.5	Surviving Chromosomes after a 50% Selection Rate…………….	109
Table 4.6	Rank Weighting………………………………………………...	110
Table 4.7	The Estimation of Risk for Knock prediction……………….........	118
Table 5.1	KMO and Bartlett's Test…………………………………...........	121
Table 5.2	Analysis of Variance (ANOVA)………………………………….	122
Table 5.3	Coefficients…………………………………………………….	123
Table 5.4	Correlations TPS, IGN, TEMP, RPM…………………………….	124
Table 5.5	Multi-collinearity problem for 4-factors…………………………..	124
Table 5.6	The Summary[b] of Model 1 for 4-Factors………………………….	125
Table 5.7	Multi-collinearity problem for 3-factors…………………………..	126
Table 5.8	The Summary[b] of Model 2 for 3-Factors………………………….	127
Table 5.9	Analysis of Variance (ANOVA)………………………………….	127
Table 5.10	Multi-collinearity problem for 3-factors…………………………..	129
Table 5.11	Summary[b] of Model 3 for 3-Factors……………………….........	129
Table 5.12	Analysis of Variance (ANOVA[a])…………………………………	130
Table 5.13	Summary result for three Models…………………………………	131
Table 5.14	AIC computation results for Three models………………………..	132
Table 5.15	Some models are applied on raw data…………………………….	135
Table 5.16	Some models are applied on RPM raw data………………………	143
Table 5.17	Some models are applied on TEMP raw data……………………..	146

Table 5.18	Summary Three best models…………………………………………	150
Table 5.19	TPS effect on knocking behavior………………………………….	152
Table 5.20	RPM effect on knocking behavior……………………………...........	154
Table 5.21	TEMP effect on knocking behavior……………………………….	154
Table 5.22	Evaluation two algorithms (NWAEF & RWGA) ………………...	166
Table 5.23	Difference average for (Elmqvist, C.) Model…………………….	171
Table 5.24	Experimental cases (Elmqvist, C.)…………………………...........	171
Table 5.25	Experimental cases (Simulate Model)…………………………….	171
Table 5.26	Error Comparison between model (Elmqvist, C.) and simulation model………………………………………..........................	172
Table 5.27	Locality of a problem Proton_Turbo_Charge……………………..	173
Table 5.28	Locality of a problem Dodeg………………...…………………..	173
Table 5.29	Locality of a problem Hyundai……………………………………	174
Table 5.30	Locality of a problem KIA-Motors………………………………..	174
Table 5.31	Result of optimization Accuracy for 10 runs Dodeg engine ……...	175
Table 5.32	Result of optimization Accuracy for 10 runs Hyundai engine …...	176
Table 5.33	Result of optimization Accuracy for 10 runs KIA engine …….….	177
Table 5.34	Result of optimization Accuracy for 10 runs Proton engine …..….	178
Table 6.1	Summary analysis result for three Models………………………...	184

List of Figures

Figure 1.1	Factors of designs and engineering activities………………………..	2
Figure 1.2	Mapping from the solution space to a set of numbers………………..	4
Figure 1.3	Connection between the method and the problem…………………...	5
Figure 2.1	Basic idea of system identification: cost function relates data and model…………………………………………………………………	21
Figure 2.2	Classical optimization methods………………………………………	29
Figure 2.3	Summarized approaches of EMOO…………………………………	32
Figure 2.4	MOEA Solution Technique Classification…………………………...	44
Figure 3.1	Framework for the optimization of NMOOPs………………………	58
Figure 3.2	Tensions during the mathematical modeling process………………..	61
Figure 3.3	Summary of tensions from hypothetical experiment………………...	62
Figure 3.4	Summary of tensions related to data and scale function……………	63
Figure 3.5	Concept of SI………………………………………………………..	64
Figure 3.6	Basic idea of SI: cost function relates data and model………………	65
Figure 3.7	Summary of system identification steps……………………………..	67
Figure 3.8	Aggregation evaluation function methodology………………………	69
Figure 3.9	Basic formulation of multi-objective evaluation function…………...	74
Figure 3.10	A general multi-objective genetic optimizer…………………………	77
Figure 3.11	Flowchart optimization methodology………………………………..	78
Figure 4.1	Engine Diagnostic tool ULTRASCAN P1 (OBD II scan tool)……..	81
Figure 4.2	Fishbone Diagram (Knock problem)…………………………………	82
Figure 4.3	Bisquare Method Flowchart………………………………………….	87
Figure 4.4	Nonlinear Relationship between TPS and Knock……………………	88
Figure 4.5	Non-linear Regression Models……………………………………….	89
Figure 4.6	Best three curve fitting models for TPS……………………………...	90
Figure 4.7	Sinusoidal Curve fitting for TPS……………………………………..	90

Figure 4.8	A graph of the exponential function A = e^{b}…………………………	93
Figure 4.9	Goodness of fit measuring……………………………………………	94
Figure 4.10	Compare between Two Models (Sinusoidal vs Gaussian Model)…...	99
Figure 4.11	Mutation Procedure………………………………………………….	116
Figure 4.12	Procedure of three-fold cross validation………...…………………...	118
Figure 5.1	Normality Test for residual (Model 1)……………………………….	126
Figure 5.2	Normality Test for residual (Model 2)……………………………….	128
Figure 5.3	Normality Test for residual (Model 3)……………………………….	130
Figure 5.4	Scatter Raw Data for TPS objective………………………………….	135
Figure 5.5	3-Top Results Models for TPS objective…………………………….	136
Figure 5.6	Best fit model for TPS raw data……………………………………...	136
Figure 5.7	Test Residual Randomness for TPS fitting model…………………...	138
Figure 5.8	Convergence History for TPS factor…………………………………	139
Figure 5.9	Parameter histories for TPS factor…………………………………...	140
Figure 5.10	Confidence band and Prediction band………………………………	141
Figure 5.11	Scatter Raw Data for RPM objective………………………………...	142
Figure 5.12	Polynomial Regression Model fitted with RPM data………………..	143
Figure 5.13	Test Residual randomness for RPM fitting model…………………...	145
Figure 5.14	Scatter Raw Data for TEMP objective……………………………….	145
Figure 5.15	4-Top Results Models for TEMP objective………………………….	146
Figure 5.16	Sinusoidal Regression Model fitted with RPM data…………………	147
Figure 5.17	Test Residual randomness for TEMP fitting model………………….	149
Figure 5.18	convergence history for TEMP factor………………………………..	149
Figure 5.19	Parameter histories for TEMP factor………………………………...	140
Figure 5.20	Effects TPS with different (Temp.) on knocking…………………….	152
Figure 5.21	Effects RPM with different (Temp.) on knocking…………………...	153
Figure 5.22	Effects TEMP with different (RPM) on knocking…………………...	155
Figure 5.23	Total Error between Propose and Real Models………………………	168
Figure 5.24	Comparison between model (Douaud and Eyzat) and (Elmqvist, C.).	170
Figure 6.1	Breakdown of articles by primary metaheuristic methods…………...	184

List of Appendices

Appendix A:	Result of Proton turbo-charge……………………………………….	201
Appendix B:	Result of KIA Motors Sorento………………………………………	203
Appendix C:	Result of Hyundai-Genesis………………………………………….	205
Appendix D:	Result of Dodge…………………………………………………..….	207
Appendix E:	Data sets ……………………………………………………..….....	210

List of Abbreviations

AIC	Akaik Information Criterion
ANOVA	Analysis of Variance
AEF	Aggregate Evaluation Function
AEFM	Aggregate Evaluation Function Model
AFPE	Akaike's Final Prediction Error
AOFBPD	Aggregate of Objective Function-based Partial Derivative
CEP	Curve Expert Professional
CF	Curve Fitting
DOF	Degree Of Freedom
DM	Decision Making
ECU	Electronic Control Unit
EF	Evaluation Function
GAs	Genetic Algorithms
GCVC	Generalized Cross-Validation Criterion
GOF	Goodness Of Fit
IGN	Ignition Timing
kn	Knock
LSE	Least Square Error
ma	vector containing row numbers of mother chromosomes
MOOPs	Multi-Objective Optimization Problems
MOEF	Multi-objective Evaluation Function
MSE	Mean Square Error
N_{bits}	N_{gene} * N_{par}. : Number of bits in the chromosome
N_{var}	Number of variables
N_{gene}	Number of bits in the gene
N_{keep}	Number of chromosomes in the mating pool

N_{pop}	Number of chromosomes in the population
NMOEF	Nonlinear Multi-objective Evaluation Function
NMOOPs	Nonlinear Multi-Objective Optimization Problems
pa	vector containing row numbers of father chromosomes
PD	partial Derivative
Rpm	Revolution Per Minute
RMS	Root Mean Square error or Standard error
SI	System Identification
SI	Spark Ignition
SNOPs	Single Nonlinear Objective Problems
SSE	Sum of Square Error
SST	Total Sum of Squares
Temp.	Temperature
Tps	Throttle position sensor
Varhi1	Highest number in the variable range
Varlo1	Lowest number in the variable range
VIF	Variance Inflation Factor
WSOF	Weighted Sum of Objective Functions
X_{rate}	Crossover rate

CHAPTER ONE
INTRODUCTION

1.1 Background

Global optimization aims to find a solution for obtaining the global minimum (maximum) objective function. In other words, global optimization aims to determine not merely "a local minimum," but also "the smallest local minimum" with respect to the solution set. In the study of the problems of optimization, the focus is to look for optimal or near optimal solutions related to the goals stipulated (Rothlauf, 2011).

Problems in the sphere of global optimization refer to the optima of nonlinear functions being characterized and computed. These problems are common within the mathematical modelling of real systems and are found in a large array of applications. A huge number of theoretical, computational and algorithmic contributions have evolved over the past few decades, which have led to the solution of many global issues involving essential practical application.

When a non-linear relationship exists between entities, changes to one of those entities will not result in a change to the other entity. This means that the relationship that exists between the two entities can be considered unpredictable. Non-linear entities may possess relations that appear rather predictable but are more complex compared to linear relationships.

Optimization problems have been considered crucial because of their visibility and strength. All designs and engineering activities have multiple objectives because they are

The contents of the thesis is for internal user only

REFRENCES

Aarts, d. i. R. G. K. M. (2011). System Identification and Parameter Estimation (edition: 2011/2012 ed.). University of Twente / Faculty of Engineering Technology / Mechanical Automation and Mechatronics.

Adra, S. F., Griffin, I., & Fleming, P. J. (2009). A convergence acceleration technique for multiobjective optimisation *Multi-Objective Memetic Algorithms* (pp. 183-205): Springer.

Ahmad, H. A. (2012). The best candidates method for solving optimization problems. *Journal of Computer Science, 8*(5), 711.

Ahmadi, M. (2007). Intake, exhaust and valve timing design using single and multi-objective genetic algorithm: SAE Technical Paper.

Aho, K., Derryberry, D., & Peterson, T. (2014). Model selection for ecologists: the worldviews of AIC and BIC. *Ecology, 95*(3), 631-636.

Akaike, H. (1998). Information theory and an extension of the maximum likelihood principle *Selected Papers of Hirotugu Akaike* (pp. 199-213): Springer.

Al-Duwaish, H. (1997). *Control of nonlinear dynamical systems using genetic algorithms*.

Amouzgar., K. (2012). *Multi-Objective Optimization using Genetic Algorithms.*

Arora, J., Huang, M., & Hsieh, C. (1994). Methods for optimization of nonlinear problems with discrete variables: a review. *Structural optimization, 8*(2-3), 69-85.

Athan, T. W., & Papalambros, P. Y. (1996). A note on weighted criteria methods for compromise solutions in multi-objective optimization. *Engineering Optimization, 27*(2), 155-176.

Attar, A. A., & Karim, G. (1998). An analytical approach for the optimization of a SI engine performance including the consideration of knock: SAE Technical Paper.

Bandyopadhyay, S., & Saha, S. (2012). *Unsupervised classification: similarity measures, classical and metaheuristic approaches, and applications*: Springer Science & Business Media.

Bandyopadhyay, S., & Saha, S. (2013). Some single-and multiobjective optimization techniques *Unsupervised Classification* (pp. 17-58): Springer.

Beck, D. J., & Chaffin, D. (1992). An evaluation of inverse kinematics models for posture prediction. *Computer Applications in Ergonomics, Occupational safety and health*, 329-336.

Benson, H. P. (1995). Concave minimization: theory, applications and algorithms *Handbook of global optimization* (pp. 43-148): Springer.

Biegler, L. T. (2010). *Nonlinear programming: concepts, algorithms, and applications to chemical processes* (Vol. 10): SIAM.

Bonissone, P. P., Subbu, R., Eklund, N., & Kiehl, T. R. (2006). Evolutionary algorithms+ domain knowledge= real-world evolutionary computation. *Evolutionary Computation, IEEE Transactions on, 10*(3), 256-280.

Bozdogan, H. (2000). Akaike's information criterion and recent developments in information complexity. *Journal of mathematical psychology, 44*(1), 62-91.

Bozza, F., De Bellis, V., & Siano, D. (2014). A Knock Model for 1D Simulations Accounting for Cyclic Dispersion Phenomena: SAE Technical Paper.

Brecq, G., Bellettre, J., & Tazerout, M. (2003). A new indicator for knock detection in gas SI engines. *International Journal of Thermal Sciences, 42*(5), 523-532.

Caminiti, S., & Petreschi, R. (2005). String coding of trees with locality and heritability *Computing and Combinatorics* (pp. 251-262): Springer.

Carrejo, D. J., & Marshall, J. (2007). What is mathematical modelling? Exploring prospective teachers' use of experiments to connect mathematics to the study of motion. *Mathematics Education Research Journal, 19*(1), 45-76.
Cavina, N., Corti, E., Minelli, G., Moro, D., & Solieri, L. (2006). Knock indexes normalization methodologies: SAE Technical Paper.
Ching-Lai, H., & Abu, S. M. M. (1979). *Multiple Objective Decision Making, Methods and Applications: A State-of-the-art Survey*: Springer-Verlag.
Coello. (1996). An empirical study of evolutionary techniques for multiobjective optimization in engineering design.
Coello. (1999). A comprehensive survey of evolutionary-based multiobjective optimization techniques. *Knowledge and Information systems, 1*(3), 269-308.
Coello. (2000). *Handling preferences in evolutionary multiobjective optimization: A survey.* Paper presented at the Evolutionary Computation, 2000. Proceedings of the 2000 Congress on.
Coello. (2001). *A short tutorial on evolutionary multiobjective optimization.* Paper presented at the Evolutionary Multi-Criterion Optimization.
Coello, & Christiansen, A. D. (1998). Two new GA-based methods for multiobjective optimization. *Civil Engineering Systems, 15*(3), 207-243.
Coello, Lamont, G. B., & Van Veldhuizen, D. A. (2007). *Evolutionary algorithms for solving multi-objective problems*: Springer Science & Business Media.
Coello Coello, C. A. (2001). A Short Tutorial on Evolutionary Multiobjective Optimization.
Colby, M. K. (2013). *Theory and applications of difference evaluation functions.* Paper presented at the Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems.
Corti, E., & Forte, C. (2011). *Real-Time Combustion Phase Optimization of a PFI Gasoline Engine*. http://dx.doi.org/10.4271/2011-01-1415
Cottrell, A. (2003). Regression analysis: basic concepts. *Available: Regression. pd*.
Dahleh, M. A. (2011). System Identification: MIT Lectures Notes 6.435-Lecture.
Dao, T. T. (2010). *Optimization And Control Of A Dynamical Process By Genetic Algorithm.* Paper presented at the ECMS.
Das, & Dennis, J. E. (1997). A closer look at drawbacks of minimizing weighted sums of objectives for Pareto set generation in multicriteria optimization problems. *Structural optimization, 14*(1), 63-69.
Das, & SENGUPTA, A. K. (1995). Technical note. Computer-aided human modelling programs for workstation design. *Ergonomics, 38*(9), 1958-1972.
Deb, K. (1999). *Solving goal programming problems using multi-objective genetic algorithms.* Paper presented at the Evolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on.
Deb, K., Agrawal, S., Pratap, A., & Meyarivan, T. (2000). A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. *Lecture notes in computer science, 1917*, 849-858.
Devijver, P. A., & Kittler, J. (1982). *Pattern recognition: A statistical approach* (Vol. 761): Prentice-Hall London.
di Gaeta, A., Giglio, V., Police, G., Reale, F., & Rispoli, N. (2010). Modeling Pressure Oscillations under Knocking Conditions: A Partial Differential Wave Equation Approach: SAE Technical Paper.
Dias, A. H., & De Vasconcelos, J. A. (2002). Multiobjective genetic algorithms applied to solve optimization problems. *Magnetics, IEEE Transactions on, 38*(2), 1133-1136.

Diener. (1995). Trajectory methods in global optimization *Handbook of Global optimization* (pp. 649-668): Springer.

Dill, K., Phillips, A., & Rosen, J. (1997). Molecular structure prediction by global optimization *Developments in Global Optimization* (pp. 217-234): Springer.

Dong, Z., Xu, J., Zou, N., & Chai, C. (2008). *Posture prediction based on orthogonal interactive genetic algorithm.* Paper presented at the Natural Computation, 2008. ICNC'08. Fourth International Conference on.

Douaud, A., & Eyzat, P. (1978). Four-octane-number method for predicting the anti-knock behavior of fuels and engines: SAE Technical Paper.

Draper, C. S. (1934). *The physical effects of detonation in a closed cylindrical chamber*: National Advisory Committee for Aeronautics.

Droste, S., & Wiesmann, D. (2003). On the design of problem-specific evolutionary algorithms *Advances in evolutionary computing* (pp. 153-173): Springer.

Dym, C. (2004). *Principles of mathematical modeling*: Academic press.

Elmqvist, C., Lindström, F., Ångström, H.-E., Grandin, B., & Kalghatgi, G. (2003). Optimizing engine concepts by using a simple model for knock prediction: SAE Technical Paper.

Eltaher, A. A. (2013). Localization of Engine Knock Events in Combustion Chambers Based on Mathematical-Physical Model of Motor Structure and Pressure Wave Propagation.

Faraway, J. J., Zhang, X., & Chaffin, D. B. (1999). Rectifying postures reconstructed from joint angles to meet constraints. *Journal of Biomechanics, 32*(7), 733-736.

Field, A. (2009). *Discovering statistics using SPSS*: Sage publications.

Floudas, C. A. (1999). *Deterministic global optimization* (Vol. 37): Springer.

Fonseca, C. M., & Fleming, P. J. (1993). *Genetic Algorithms for Multiobjective Optimization: FormulationDiscussion and Generalization.* Paper presented at the ICGA.

Franz, R. (2006). Representations for genetic and evolutionary algorithms: Springer–Verlag, Berling, Heidelberg, Netherlands.

Freschi, F., & Repetto, M. (2005). Multiobjective optimization by a modified artificial immune system algorithm *Artificial Immune Systems* (pp. 248-261): Springer.

Gabli, M., Jaara, E. M., & Mermri, E. B. (2014). A Genetic Algorithm Approach for an Equitable Treatment of Objective Functions in Multi-objective Optimization Problems. *IAENG International Journal of Computer Science, 41*(2).

Ganestam, P. (2010). *Empirical Knock Model for Automatic Engine Calibration.* M. Sc Thesis, Lund University.

Geisser, S. (1993). *Predictive inference* (Vol. 55): CRC Press.

Gen, & Cheng, R. (1997). Genetic algorithms and engineering design, 1997. *John Wily and Sons, New York*.

Gen, Ida, K., Li, Y., & Kubota, E. (1995). Solving bicriteria solid transportation problem with fuzzy numbers by a genetic algorithm. *Computers & Industrial Engineering, 29*(1), 537-541.

Glover, F., & Laguna, M. (1997). Tabu search, 1997. *Kluwer Academic Publishers*.

Golberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. *Addion wesley, 1989*.

Gottlieb, J., Julstrom, B. A., Raidl, G. R., & Rothlauf, F. (2001). *Prüfer numbers: A poor representation of spanning trees for evolutionary search.* Paper presented at the Proceedings of the Genetic and Evolutionary Computation Conference.

Gottlieb, J., & Raidl, G. R. (2000). *The Effects of Locality on the Dynamics of Decoder-Based Evolutionary Search.* Paper presented at the GECCO.

Griffin, M. J. (2001). The validation of biodynamic models. *Clinical Biomechanics, 16*, S81-S92.

Grodzevich, O., & Romanko, O. (2006). Normalization and other topics in multi-objective optimization.

Haftka, R. T., & Gürdal, Z. (1992). *Elements of structural optimization* (Vol. 11): Springer Science & Business Media.

Hajela, P., & Lin, C.-Y. (1992). Genetic search strategies in multicriterion optimal design. *Structural optimization, 4*(2), 99-107.

Hansen, E. (1992). Global optimization using interval analysis, 1992. *Marcel Dekkar, New York, NY*.

Harishchandra, J., Ravindra, K., Sachin, B., & Thiyagarajan, S. (2010). Optimisation of Engine Cooling for Knock Suppression of Turbocharged Gasoline Engine.

Haupt, R. L., & Haupt, S. E. (2004). *Practical genetic algorithms*: John Wiley & Sons.

Herwijnen, M. v. (2011). Weighted Summation, www.ivm.vu.nl/en/Images/MCA2_tcm234-161528.pdf.

Hichert, J., Hoffmann, A., & Phú, H. X. (1997). Convergence speed of an integral method for computing the essential supremum *Developments in global Optimization* (pp. 153-170): Springer.

Horan, & Lavelle. (2005). Introduction to Partial Differentiation (Version 1.0 ed., pp. 30): PlymouthUniversity.

Horn, J. (1997). F1. 9 Multicriterion decision making. *Handbook of Evolutionary Computation, 97*(1).

Horn, J., Nafpliotis, N., & Goldberg, D. E. (1994). *A niched Pareto genetic algorithm for multiobjective optimization.* Paper presented at the Evolutionary Computation, 1994. IEEE World Congress on Computational Intelligence., Proceedings of the First IEEE Conference on.

Horst, & Romeijn. (2002). *Handbook of global optimization* (Vol. 2): Springer.

Horst, & Tuy. (1996a). *Global optimization: Deterministic approaches*: Springer.

Horst, & Tuy. (1996b). Global optimization: deterministic approaches. 1996. *Springer: Berlin). Horst, R. and Pardalos MP, Handbook of global optimization, l995 (Kluwer Academic Publishers: London). Ichida, K., Constrained optimization using interval analysis, Computers ind. Engng, 31*(3), 4.

Horst, R., & Romeijn, H. E. (2002). *Handbook of global optimization* (Vol. 2): Springer.

Howard, B., Cloutier, A., & Yang, J. J. (2012). Physics-based seated posture prediction for pregnant women and validation considering ground and seat pan contacts. *Journal of biomechanical engineering, 134*(7), 071004.

Hu, & Mehrotra, S. (2012). Robust and stochastically weighted multiobjective optimization models and reformulations. *Operations research, 60*(4), 936-953.

Hu, S. (2007). Akaike information criterion. *Center for Research in Scientific Computation*.

Hwang, C.-L., & Masud, A. S. M. (1979). *Multiple objective decision making—methods and applications*.

Igel, C. (1998). *Causality of hierarchical variable length representations.* Paper presented at the Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on.

Ismail, F. S., & Yusof, R. (2010). *A new self organizing multi-objective optimization method.* Paper presented at the Systems Man and Cybernetics (SMC), 2010 IEEE International Conference on.

Jakob, W., Gorges-Schleuter, M., & Blume, C. (1992). *Application of Genetic Algorithms to Task Planning and Learning.* Paper presented at the Parallel Problem Solving from Nature 2, PPSN-II, Brussels, Belgium, September 28-30, 1992.

Jaszkiewicz, A., Hapke, M., & Kominek, P. (2001). *Performance of multiple objective evolutionary algorithms on a distribution system design problem-Computational experiment.* Paper presented at the Evolutionary Multi-Criterion Optimization.

Jing, H. (2005). Local evaluation functions and global evaluation functions for computational evolution.

Jing, H., & Qingsheng, C. (2003). Emergence from local evaluation function. *Journal of Systems Science and Complexity, 16*(3), 372-390.

Joaquim, P., & Marques, S. (2007). Applied statistics using SPSS, statistica, Matlab and R. *Springer Company USA*, 205-211.

Jones, Brown, R. D., Clark, D. E., Willett, P., & Glen, R. C. (1993). *Searching databases of two-dimensional and three-dimensional chemical structures using genetic algorithms.* Paper presented at the Proceedings of the 5th International Conference on Genetic Algorithms.

Jones, Mirrazavi, S. K., & Tamiz, M. (2002). Multi-objective meta-heuristics: An overview of the current state-of-the-art. *European journal of operational research, 137*(1), 1-9.

Jubril, A. M. (2012). A nonlinear weights selection in weighted sum for convex multiobjective optimization. *Facta Universitatis, 27*(3), 357-372.

Jung, E. S., & Choe, J. (1996). Human reach posture prediction based on psychophysical discomfort. *International Journal of Industrial Ergonomics, 18*(2), 173-179.

Jung, E. S., & Park, S. (1994). Prediction of human reach posture using a neural network for ergonomic man models. *Computers & Industrial Engineering, 27*(1), 369-372.

Kasseris, E. P. (2011). *Knock limits in spark ignited direct injected engines using gasoline/ethanol blends.* Massachusetts Institute of Technology.

Kearfott. (1996). Rigorous Global Search: Continuous Problems Kluwer Academic Publishers. *Dordrecht, Netherlands*.

Khalil, S., Camal, R., & Laurent, T. (2009). Description of Knock Limit in a CFR Engine: Effects of Engine Settings and Gas Quality: SAE Technical Paper.

Khan, S. U. (2009). *A Self-adaptive Weighted Sum Technique for the Joint Optimization of Performance and Power Consumption in Data Centers.* Paper presented at the ISCA PDCCS.

Kim, Martin, B. J., & Gillespie, R. B. (2004). Modeling the coordinated movements of the head and hand using differential inverse kinematics: SAE Technical Paper.

Kim, & Weck, O. (2005). Adaptive weighted-sum method for bi-objective optimization: Pareto front generation. *Structural and multidisciplinary optimization, 29*(2), 149-158.

Kim, & Weck, O. (2006). Adaptive weighted sum method for multiobjective optimization: a new method for Pareto front generation. *Structural and multidisciplinary optimization, 31*(2), 105-116.

Knowles, J., & Hughes, E. J. (2005). *Multiobjective optimization on a budget of 250 evaluations.* Paper presented at the Evolutionary Multi-Criterion Optimization.

Kohavi, R. (1995). *A study of cross-validation and bootstrap for accuracy estimation and model selection.* Paper presented at the Ijcai.

Konak, A., Coit, D. W., & Smith, A. E. (2006). Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety, 91*(9), 992-1007.

Kozarac, D., Tomic, R., Taritas, I., Chen, J.-Y., & Dibble, R. W. (2015). A Model for Prediction of Knock in the Cycle Simulation by Detail Characterization of Fuel and Temperature Stratification. *SAE International Journal of Engines, 8*(2015-01-1245).

Kuhn, H., & Tucker, A. (1951). Proceedings of the 2nd Berkeley Symposium on Mathematical Statistics and Probability: University of California Press.

Levy, A. V., & Gómez, S. (1985). The tunneling method applied to global optimization. *Numerical optimization, 1981*, 213-244.

Liu, Begg, D., & Fishwick, R. (1998). Genetic approach to optimal topology/controller design of adaptive structures. *International Journal for Numerical Methods in Engineering, 41*(5), 815-830.

Liu, Li, W., Wu, T. B., Cheng, Y., Zhou, T. Y., & Zhu, G. F. (2014). *An Improved Constrained Optimization Multi-Objective Genetic Algorithm and its Application in Engineering.* Paper presented at the Advanced Materials Research.

Liu, G., & Chen, J. (2011). *The application of genetic algorithm based on matlab in function optimization.* Paper presented at the Electrical and Control Engineering (ICECE), 2011 International Conference on.

Ljung, L. (2010). Perspectives on system identification. *Annual Reviews in Control, 34*(1), 1-12.

Lochau, D.-I. M., Sun, B., Goltz, U., & Huhn, P. (2010). Model-based Parameter Optimization of an Engine Control Unit using Genetic Algorithms.

Lohmann, R. (1993). Structure evolution and incomplete induction. *Biological Cybernetics, 69*(4), 319-326.

Lonari, Y. (2011). Stochastic knock detection model for spark ignited engines.

Luke, S. (2015). Essentials of Metaheuristics. A Set of Undergraduate Lecture Notes. (Online Version 2.2). Department of Computer Science, George Mason University, October 2014. 261 p.

Luna, F., Nebro, A. J., & Alba, E. (2006). Parallel evolutionary multiobjective optimization *Parallel Evolutionary Computations* (pp. 33-56): Springer.

Ma, B. (2001). *Parametric and nonparametric approaches for multisensor data fusion.* The University of Michigan.

Maier, M. W., & Rechtin, E. (2000). *The art of systems architecting* (Vol. 2): CRC press Boca Raton.

Marler, R. T., & Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. *Structural and multidisciplinary optimization, 41*(6), 853-862.

Merola, S., Sementa, P., & Tornatore, C. (2011). Experiments on knocking and abnormal combustion through optical diagnostics in a boosted spark ignition port fuel injection engine. *International journal of automotive technology, 12*(1), 93-101.

Messac, A., & Mattson, C. A. (2002). Generating well-distributed sets of Pareto points for engineering design using physical programming. *Optimization and Engineering, 3*(4), 431-450.

Michalewicz, Z. (1996). *Genetic algorithms+ data structures= evolution programs*: springer.

Michalewicz, Z., Schmidt, M., Michalewicz, M., & Chiriac, C. (2005). *Evaluation functions for real world problems: A case study.* Paper presented at the Proceedings of the 16th Mini–EURO Conference and 10th Meeting of EWGT.

Millo, F., Rolando, L., Pautasso, E., & Servetto, E. (2014). A Methodology to Mimic Cycle to Cycle Variations and to Predict Knock Occurrence through Numerical Simulation: SAE Technical Paper.

Mockus, J. (2002). Bayesian heuristic approach to global optimization and examples. *Journal of Global Optimization, 22*(1-4), 191-203.

Mockus, J. (2010). *Bayesian Heuristic approach to discrete and global optimization: Algorithms, visualization, software, and applications*: Springer-Verlag.

Mockus, J., Eddy, W., Mockus, A., Mockus, L., & Reklaitis, G. (1996). Bayesian Heuristic Approach to Discrete and Global Optimization: Algorithms, Visualization. *Software, and Applications. Kluwer Academic Publishers, Dordrecht*.

Moré, J. J., & Wu, Z. (1997). Global continuation for distance geometry problems. *SIAM Journal on Optimization, 7*(3), 814-836.

Mosteller, F., & Doob, L. W. (1949). *The pre-election polls of 1948*: Social Science Research Council.

Murata, T., & Ishibuchi, H. (1995). *MOGA: Multi-objective genetic algorithms.* Paper presented at the Evolutionary Computation, 1995., IEEE International Conference on.

Murata, T., Ishibuchi, H., & Tanaka, H. (1996). Multi-objective genetic algorithm and its applications to flowshop scheduling. *Computers & Industrial Engineering, 30*(4), 957-968.

Nedjah, N., & de Macedo Mourelle, L. (2005). *Real-world multi-objective system engineering*: Nova Publishers.

Neumaier. (1990). *Interval methods for systems of equations* (Vol. 37): Cambridge university press.

Nowak, R. D. (2002). Nonlinear system identification. *Circuits, Systems and Signal Processing, 21*(1), 109-122.

Osman, I. H., & Kelly, J. P. (1996). *Meta-heuristics: theory and applications*: Springer.

Paduart, J. (2008). *Identification of Nonlinear Systems using Polynomial Nonlinear State Space Models.*

Paduart, J., Lauwers, L., Swevers, J., Smolders, K., Schoukens, J., & Pintelon, R. (2010). Identification of nonlinear systems using polynomial nonlinear state space models. *Automatica, 46*(4), 647-656.

Paulden, T., & Smith, D. K. (2006). From the Dandelion Code to the Rainbow Code: A class of bijective spanning tree representations with linear complexity and bounded locality. *Evolutionary Computation, IEEE Transactions on, 10*(2), 108-123.

Peyton. (2014). New Approaches to Knock Simulation, Analysis, and Control. [Presentation].

Peyton Jones, J. C., Spelina, J. M., & Frey, J. (2013). Likelihood-based control of engine knock. *Control Systems Technology, IEEE Transactions on, 21*(6), 2169-2180.

Pham, Q., & Coulter, S. (1995). *Modelling the chilling of pig carcasses using an evolutionary method.* Paper presented at the Proc. Int. Congress of Refrig.

Pintér. (1996a). Global optimization in action. Continuous and Lipschitz optimization: Algorithms, implementation and applications: Kluwer, Dordrecht.

Pintér. (1996b). *Global optimization in action: continuous and Lipschitz optimization: algorithms, implementations and applications* (Vol. 6): Springer.

Pro, I. (2007). Version 6.0, WaveMetrics: Inc.

Puchta, M., & Gottlieb, J. (2002). Solving car sequencing problems by local optimization *Applications of Evolutionary Computing* (pp. 132-142): Springer.

Rachmawati, L., & Srinivasan, D. (2006). *A multi-objective genetic algorithm with controllable convergence on knee regions.* Paper presented at the Evolutionary Computation, 2006. CEC 2006. IEEE Congress on.

Raidl, G. R., & Gottlieb, J. (2005). Empirical analysis of locality, heritability and heuristic bias in evolutionary algorithms: A case study for the multidimensional knapsack problem. *Evolutionary computation, 13*(4), 441-475.

Ratschek, H., & Rokne, J. (1988). *New computer methods for global optimization*: Halsted Press.

Rechenberg, I. (1994). Evolutionsstrategie'94, volume 1 of Werkstatt Bionik und Evolutionstechnik. *Frommann {Holzboog, Stuttgart*.

Reeves, C. R. (1995). Modern heuristic techniques for combinatorial problems. 1995: McGraw-Hill International Limited UK.

Revier, B. M. (2006). *Phenomena that determine knock onset in spark-ignited engines.* Massachusetts Institute of Technology.

Richardson, J. T., Palmer, M. R., Liepins, G. E., & Hilliard, M. (1989). *Some guidelines for genetic algorithms with penalty functions.* Paper presented at the Proceedings of the third international conference on Genetic algorithms.

Rothlauf, F. (2011). *Design of modern heuristics: principles and application*: Springer.

Rothlauf, F., & Goldberg, D. (1999). *Tree network design with genetic algorithms-an investigation in the locality of the prüfernumber encoding.* Paper presented at the Late Breaking Papers at the Genetic and Evolutionary Computation Conference.

Ryu, J.-h., Kim, S., & Wan, H. (2009). *Pareto front approximation with adaptive weighted sum method in multiobjective simulation optimization.* Paper presented at the Winter Simulation Conference.

Saaty, T. L., & Vargas, L. (1991). The Logic of Priorities. Applications of the Analytic Hierarchy Process in Business, Energy, Health & Transportation, Vol. III of the AHP Series: RWS Publications, Pittsburgh.

Santana-Quintero, L. V., Montano, A. A., & Coello, C. A. C. (2010). A review of techniques for handling expensive functions in evolutionary multi-objective optimization *Computational intelligence in expensive optimization problems* (pp. 29-59): Springer.

Sarker, R. A., & Newton, C. S. (2007). *Optimization modelling: a practical approach*: CRC Press.

Schaffer, J. D. (1985). *Multiple objective optimization with vector evaluated genetic algorithms.* Paper presented at the Proceedings of the 1st international Conference on Genetic Algorithms.

Schneeweiss, C. (2003). *Distributed decision making*: Springer.

Sendhoff, B., Kreutz, M., & Von Seelen, W. (1997). A condition for the genotype-phenotype mapping: Causality. *arXiv preprint adap-org/9711001*.

Shan, S., & Wang, G. G. (2005). An efficient Pareto set identification approach for multiobjective optimization on black-box functions. *Journal of Mechanical Design, 127*(5), 866-874.

Sheng, W., Swift, S., Zhang, L., & Liu, X. (2005). A weighted sum validity function for clustering with a hybrid niching genetic algorithm. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 35*(6), 1156-1167.

Shih, S., Itano, E., Xin, J., Kawamoto, M., & Maeda, Y. (2003). Engine knock toughness improvement through water jacket optimization: SAE Technical Paper.

Sindhya, K. (2011). *Hybrid evolutionary multi-objective optimization with enhanced convergence and diversity.* PhD thesis, Department of Mathematical Information Technology, University of Jyväskylä, Finland.

Spelina, J. M., Jones, J. C. P., & Frey, J. (2014). Recent Advances in Knock Analysis, Simulation, and Control: SAE Technical Paper.

Srinivas, N., & Deb, K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation, 2*(3), 221-248.

Strongin, R. G., & Sergeyev, Y. D. (2000). *Global optimization with non-convex constraints: Sequential and parallel algorithms* (Vol. 45): Springer.

Sykes, A. O. (1993). An introduction to regression analysis.

Syswerda, G., & Palmucci, J. (1991). *The Application of Genetic Algorithms to Resource Scheduling.* Paper presented at the ICGA.

Taglialatela, F., Moselli, G., & Lavorgna, M. (2005). Engine knock detection and control using in-cylinder pressure signal and soft computing techniques: SAE Technical Paper.

Talbi. (2009). *Metaheuristics: from design to implementation* (Vol. 74): John Wiley & Sons.

Talbi, Basseur, M., Nebro, A. J., & Alba, E. (2012). Multi-objective optimization using metaheuristics: non-standard algorithms. *International Transactions in Operational Research, 19*(1-2), 283-305.

Tang, W., Cavazza, M., Mountain, D., & Earnshaw, R. (1999). A constrained inverse kinematics technique for real-time motion capture animation. *The Visual Computer, 15*(7), 413-425.

Tappeta, R., Renaud, J., & Rodríguez, J. (2002). An interactive multiobjective optimization design strategy for decision based multidisciplinary design. *Engineering Optimization, 34*(5), 523-544.

Tarun, P. K. (2008). *A dynamic multiple stage, multiple objective optimization model with an application to a wastewater treatment system*: ProQuest.

Thomas, C. (1996). Introduction to Differential Calculus.

Thomasson, A., Eriksson, L., Lindell, T., Peyton Jones, J. C., Spelina, J., & Frey, J. (2013). *Tuning and experimental evaluation of a likelihood-based engine knock controller.* Paper presented at the Decision and Control (CDC), 2013 IEEE 52nd Annual Conference on.

Tolani, D., Goswami, A., & Badler, N. I. (2000). Real-time inverse kinematics techniques for anthropomorphic limbs. *Graphical models, 62*(5), 353-388.

Tran, L.-N., Hanif, M. F., Tölli, A., & Juntti, M. (2012). Fast converging algorithm for weighted sum rate maximization in multicell MISO downlink. *Signal Processing Letters, IEEE, 19*(12), 872-875.

Trummer, I., & Koch, C. (2014). *Approximation schemes for many-objective query optimization.* Paper presented at the Proceedings of the 2014 ACM SIGMOD international conference on Management of data.

Vancoillie, J., Sileghem, L., & Verhelst, S. (2013). Development and validation of a knock prediction model for methanol-fuelled SI engines: SAE Technical Paper.

Voss, S., Osman, I. H., & Roucairol, C. (1999). *Meta-heuristics: Advances and trends in local search paradigms for optimization*: Kluwer Academic Publishers.

Vossoughi, & Rezazadeh, S. (2004). Development of an Integrated Computer Environment for Optimization of Engine Management System Calibration: SAE Technical Paper.

Vossoughi, & Rezazadeh, S. (2005). *Optimization of the calibration for an internal combustion engine management system using multi-objective genetic algorithms.* Paper presented at the Evolutionary Computation, 2005. The 2005 IEEE Congress on.

Wang, X. (1999). A behavior-based inverse kinematics algorithm to predict arm prehension postures for computer-aided ergonomic evaluation. *Journal of Biomechanics, 32*(5), 453-460.

Wang, X., & Verriest, J. P. (1998). A geometric algorithm to predict the arm reach posture for computer-aided ergonomic evaluation. *The journal of visualization and computer animation, 9*(1), 33-47.

Weicker, K., & Weicker, N. (1999). Locality vs. randomness–dependence of operator quality on the search state. *Foundations of Genetic Algorithms, 5*, 147-163.

Whitley, D., & Rowe, J. E. (2005). Gray, binary and real valued encodings: Quad search and locality proofs *Foundations of Genetic Algorithms* (pp. 21-36): Springer.

Wienke, D., Lucasius, C., & Kateman, G. (1992). Multicriteria target vector optimization of analytical procedures using a genetic algorithm: Part I. theory, numerical simulations and application to atomic emission spectroscopy. *Analytica Chimica Acta, 265*(2), 211-225.

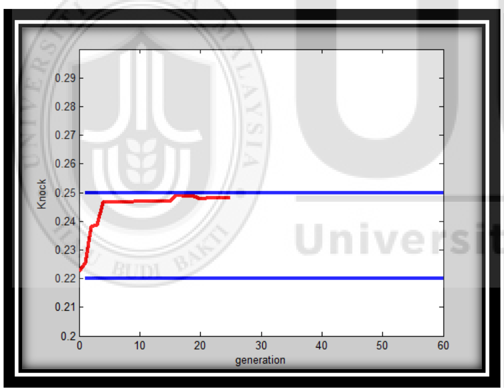
Williams, B., Brown, T., & Onsman, A. (2012). Exploratory factor analysis: A five-step guide for novices. *Australasian Journal of Paramedicine, 8*(3), 1.

Wilson, Cappelleri, D., Simpson, T. W., & Frecker, M. (2001). Efficient Pareto frontier exploration using surrogate approximations. *Optimization and Engineering, 2*(1), 31-50.
Wilson, & Macleod, M. (1993). *Low implementation cost IIR digital filter design using genetic algorithms.* Paper presented at the IEE/IEEE workshop on natural algorithms in signal processing.
Yang. (2011). Bat algorithm for multi-objective optimisation. *International Journal of Bio-Inspired Computation, 3*(5), 267-274.
Yang, Karamanoglu, M., & He, X. (2013). Multi-objective flower algorithm for optimization. *Procedia Computer Science, 18*, 861-868.
Yang, Marler, R. T., Kim, H., Arora, J., & Abdel-Malek, K. (2004). *Multi-objective optimization for upper body posture prediction.* Paper presented at the 10th AIAA/ISSMO multidisciplinary analysis and optimization conference.
Zadbood, A., & Noghondarian, K. (2012). Multiple Response Surface Optimization Considering the Decision Maker's Preference Information. *Advanced Materials Research, 433*, 1646-1652.
Zebulum, R. S., Pacheco, M. A., & Vellasco, M. (1998). *A multi-objective optimisation methodology applied to the synthesis of low-power operational amplifiers.* Paper presented at the In Ivan Jorge Cheuri and Carlos Alberto dos Reis Filho, editors, Proceedings of the XIII International Conference in Microelectronics and Packaging.
Zhang, Domaszewski, M., & Fleury, C. (2001). An improved weighting method with multibounds formulation and convex programming for multicriteria structural optimization. *International Journal for Numerical Methods in Engineering, 52*(9), 889-902.
Zhang, Han, Z.-H., Li, W.-J., & Song, W.-P. (2008). Bilevel adaptive weighted sum method for multidisciplinary multi-objective optimization. *AIAA journal, 46*(10), 2611-2622.
Zhen, X., Wang, Y., Xu, S., Zhu, Y., Tao, C., Xu, T., & Song, M. (2012). The engine knock analysis–an overview. *Applied Energy, 92*, 628-636.
Zheng, Q., & Zhuang, D. (1995). Integral global minimization: algorithms, implementations and numerical tests. *Journal of Global Optimization, 7*(4), 421-454.
Zhigljavsky, A. A., & Pintér, J. (1991). *Theory of global random search*: Springer Netherlands.
Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P. N., & Zhang, Q. (2011). Multiobjective evolutionary algorithms: A survey of the state of the art. *Swarm and Evolutionary Computation, 1*(1), 32-49.
Zitzler, E. (1999). *Evolutionary algorithms for multiobjective optimization: Methods and applications* (Vol. 63): Citeseer.
Zou, Liu, M., Kang, L., & He, J. (2004). *A high performance multi-objective evolutionary algorithm based on the principles of thermodynamics.* Paper presented at the Parallel Problem Solving from Nature-PPSN VIII.
Zou, Zhang, Q., Yang, J., Cloutier, A., Gragg, J., & Pena-Pitarch, E. (2011). *Determining weights of joint displacement objective function for standing reach tasks.* Paper presented at the First international symposium on digital human modeling, Lyon, France.
Zou, Zhang, Q., Yang, J. J., Boothby, R., Gragg, J., & Cloutier, A. (2011a). An alternative formulation for determining weights of joint displacement objective function in seated posture prediction *Digital Human Modeling* (pp. 231-242): Springer.
Zou, Zhang, Q., Yang, J. J., Cloutier, A., & Pena-Pitarch, E. (2012). Nonlinear inverse optimization approach for determining the weights of objective function in standing reach tasks. *Computers & Industrial Engineering, 63*(4), 791-801.

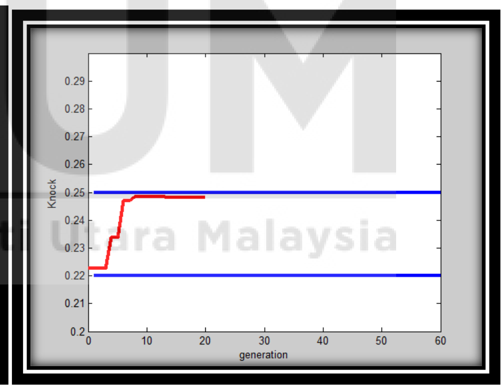
APPENDIX A

PROTON_TURBO CHARGE ENGINE

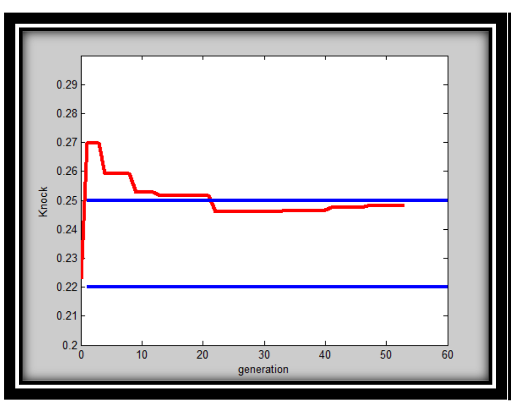
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.030314	25	0.24803	80.013	1218.1	89.905
2	0.033244	20	0.24802	80.023	1199.9	90.135
3	0.042071	53	0.24799	80.021	1205.5	91.364
4	0.053894	60	0.24721	80.012	1215.4	91.382
5	0.041634	60	0.24836	80.345	1195.7	90.504
6	0.050171	36	0.24793	80.137	1066.5	89.494
7	0.026348	4	0.24792	80.013	1217.2	89.5
8	0.044953	60	0.24741	80.02	1202.7	90.839
9	0.036225	47	0.24793	80.148	1062.6	90.499
10	0.034941	25	0.24803	80.013	1218.1	89.905
11	0.032464	20	0.24802	80.023	1199.9	90.135



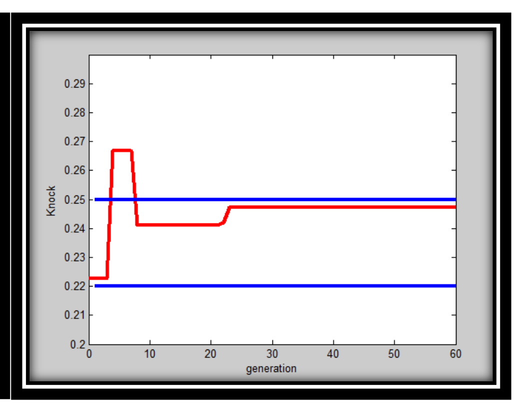
(1)



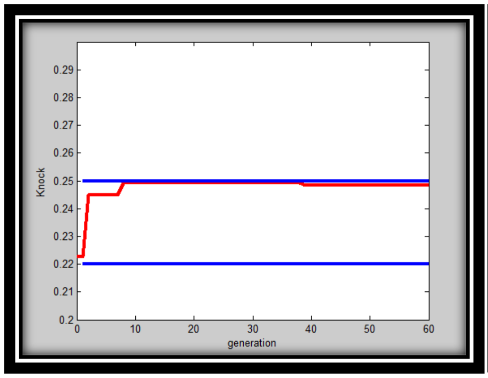
(2)



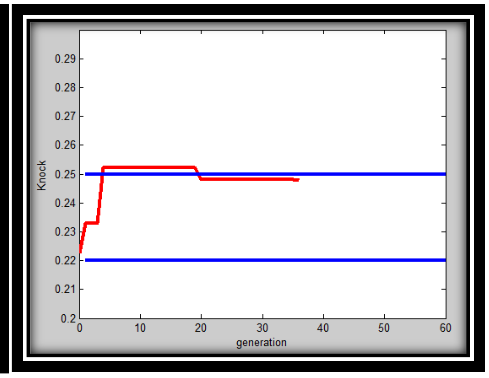
(2)



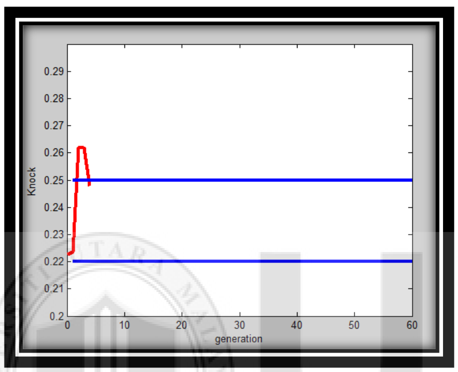
(4)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

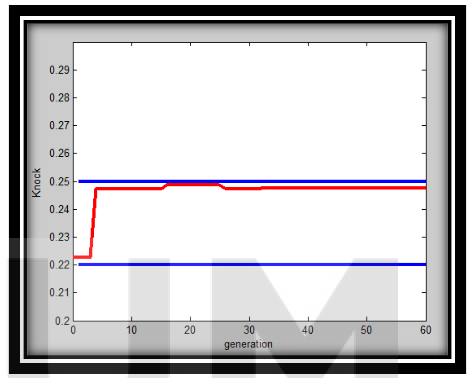
(5)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

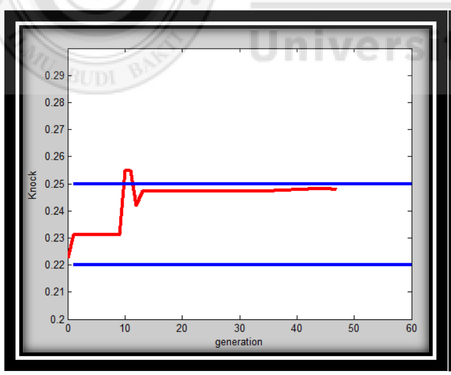
(6)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

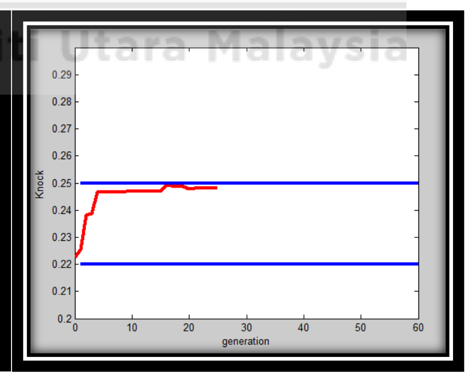
(7)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

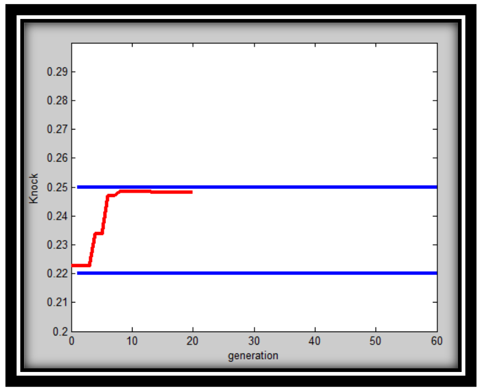
(8)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

(9)


Knock
0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
0
10
20
30
40
50
60
generation

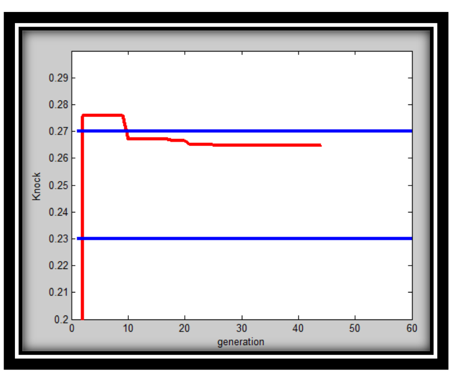
(10)



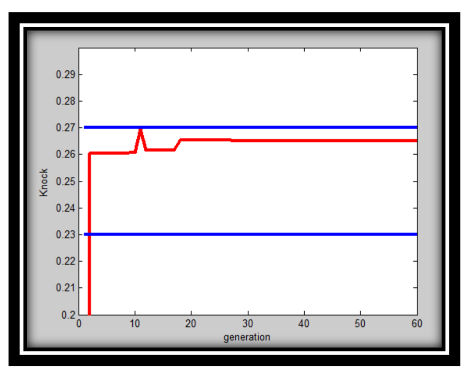
(11)

Appendix B
KIA_Motors_Sorento

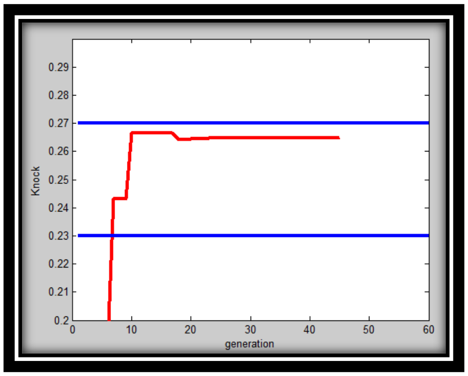
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.046865	44	0.26499	7.6713	1717.5	91.582
2	0.054338	60	0.26514	7.562	2032.3	92.55
3	0.040090	45	0.26494	7.4681	2397.3	89.915
4	0.036770	43	0.26498	7.4644	2416.2	91.174
5	0.061880	54	0.26499	7.4904	2302.2	90.591
6	0.049794	57	0.265	7.4911	2296.3	87.882
7	0.045329	60	0.26469	7.6645	1729.9	90.926
8	0.044775	53	0.26498	7.6344	1814	95.045
9	0.054044	46	0.26503	7.7019	1658	94.302
10	0.063411	60	0.26464	7.6406	1784.4	87.068



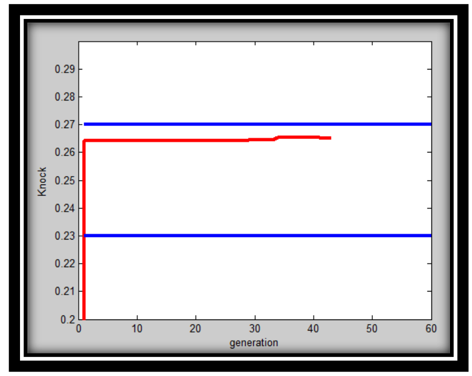
(1)



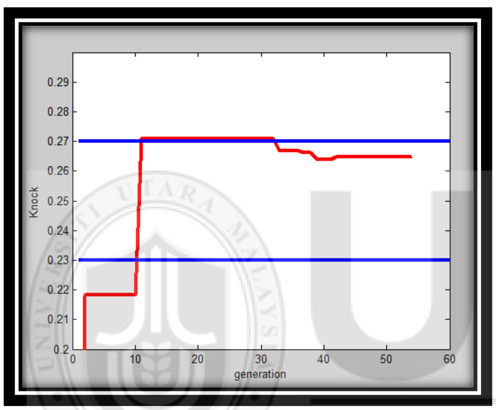
(2)


Knock
generation

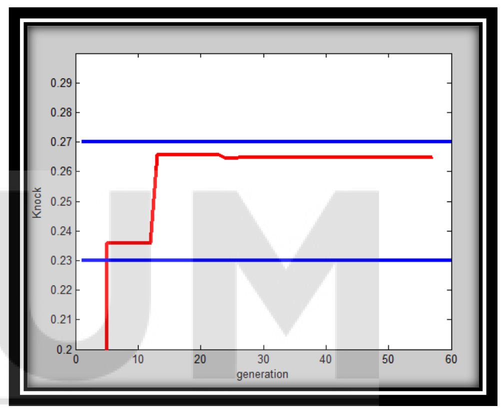
(3)


Knock
generation

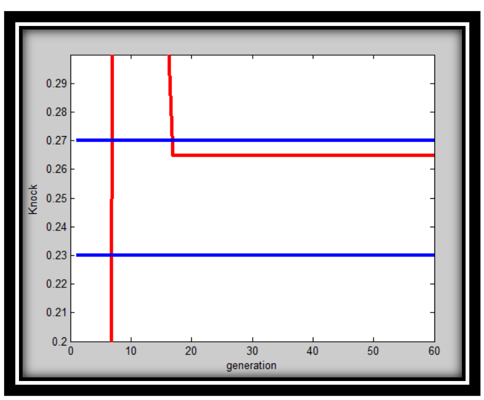
(4)


Knock
generation

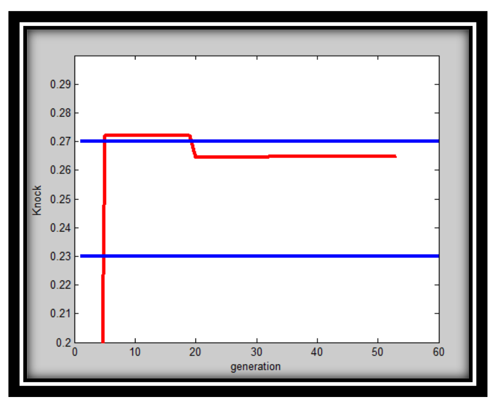
(5)


Knock
generation

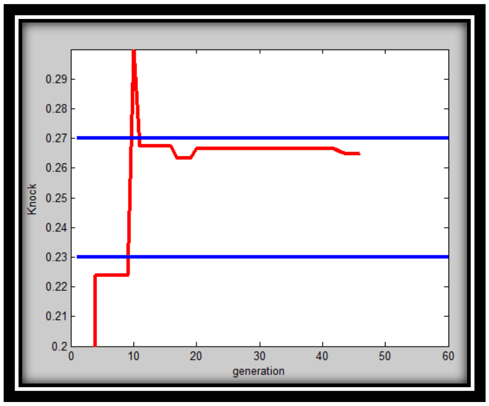
(6)


Knock
generation

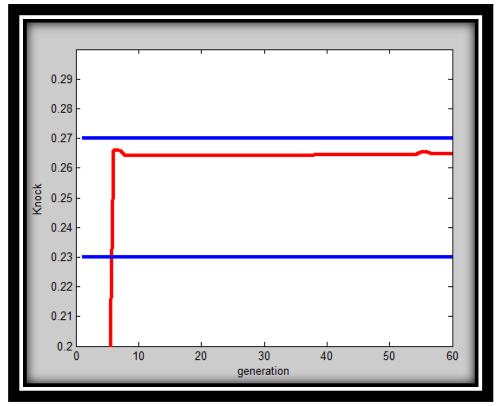
(7)


Knock
generation

(8)



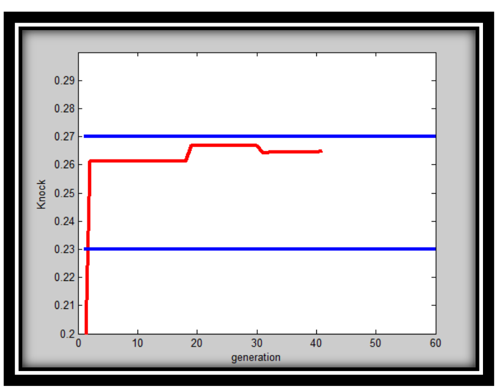
(9)



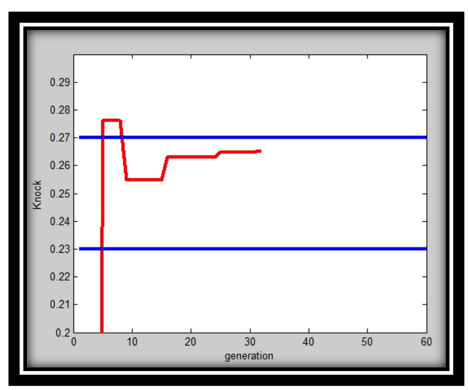
(10)

Appendix C
Hyundai_Genesis Engine

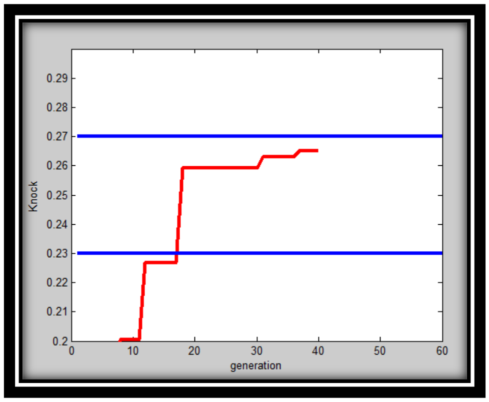
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.041626	41	0.26504	7.6469	1776.1	91.387
2	0.032792	32	0.26498	7.6585	1753.9	95.858
3	0.046630	40	0.26494	7.5212	2180.6	92.85
4	0.043320	59	0.26507	7.4781	2355.7	90.784
5	0.028497	25	0.26498	7.4744	2372.4	91.715
6	0.041442	47	0.265	7.4675	2407	94.06
7	0.028881	25	0.26499	7.5968	1918.1	92.593
8	0.036631	35	0.26507	7.6751	1704.8	87.575
9	0.038024	27	0.26504	7.7449	1576.5	88.572
10	0.033767	31	0.26496	7.5119	2214.4	90.818



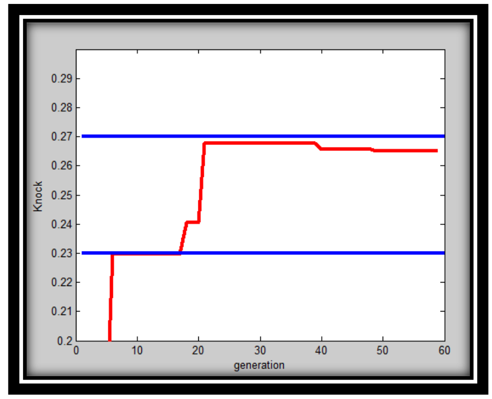
(1)



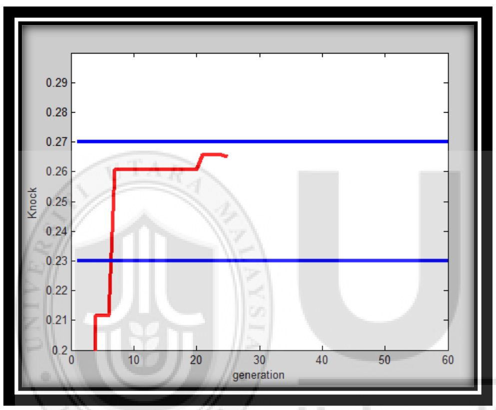
(2)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

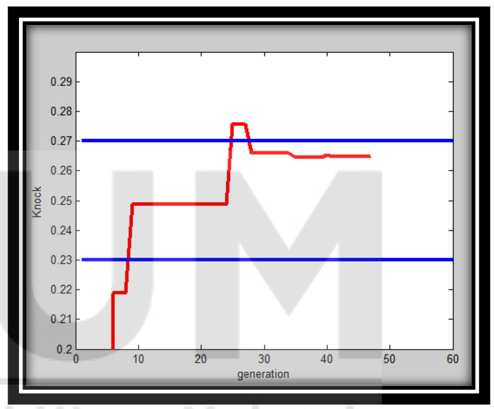
(3)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

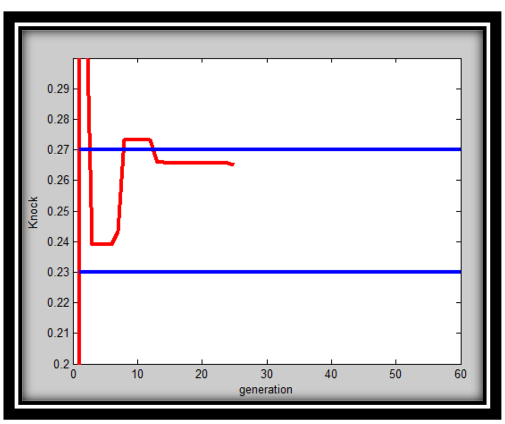
(4)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

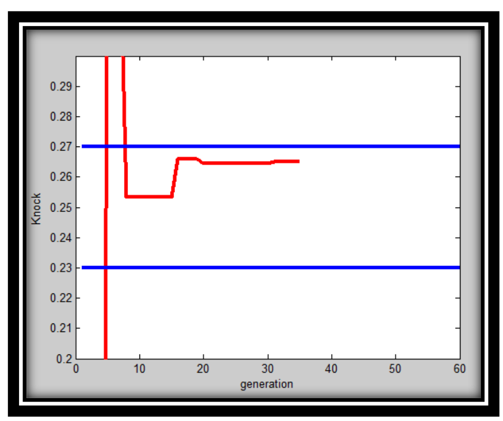
(5)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

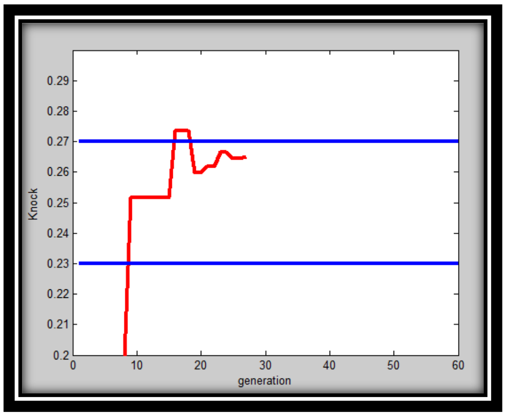
(6)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

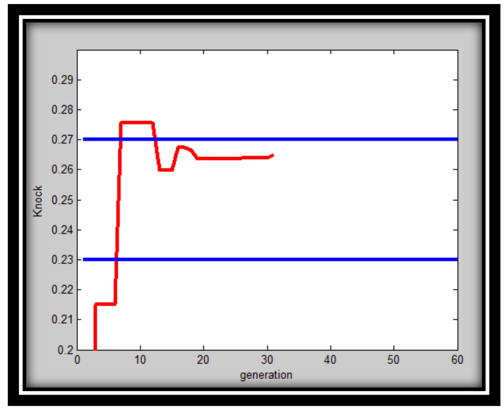
(7)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

(8)



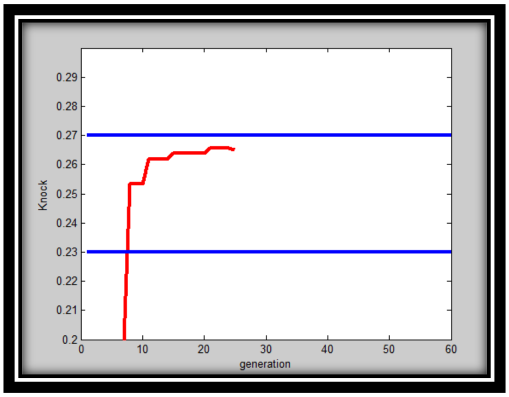
(9)



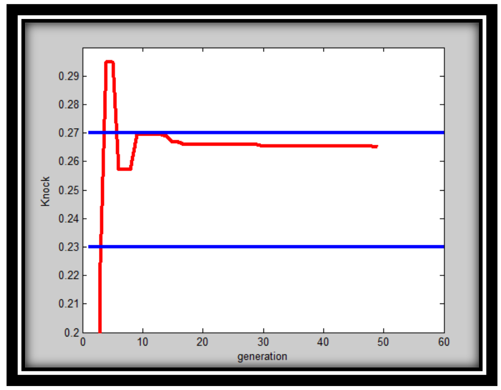
(10)

Appendix D
Dodeg Engine

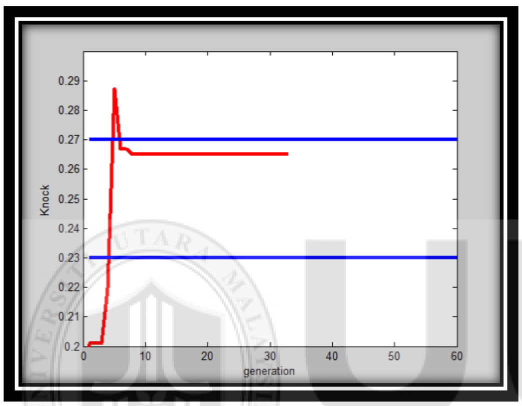
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.036748	25	0.26496	7.8568	1482.4	53.379
2	0.050063	49	0.26494	7.5149	2199.8	60.493
3	0.035558	33	0.26507	7.5659	2012.9	58.467
4	0.049124	34	0.265	7.7616	1559.9	66.594
5	0.078471	60	0.26447	7.6748	1701.7	58.603
6	0.050132	49	0.26499	7.8438	1483.9	57.734
7	0.051138	27	0.26504	8.2077	2059.7	59.7
8	0.048178	19	0.26503	7.8392	1487.5	55.217
9	0.032778	19	0.26496	7.8403	1485.8	60.848
10	0.061364	60	0.26509	8.1502	1875.4	55


Knock
generation

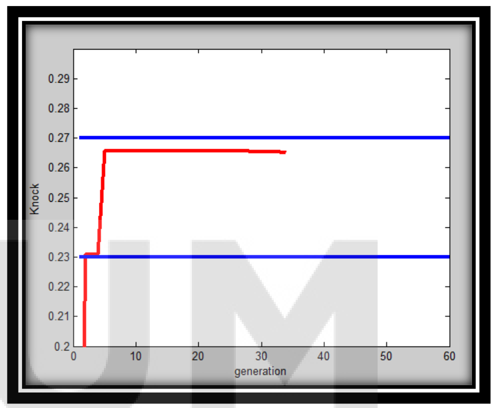
(1)


Knock
generation

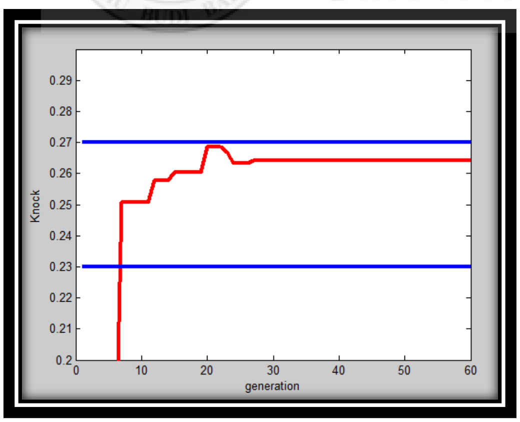
(2)


Knock
generation

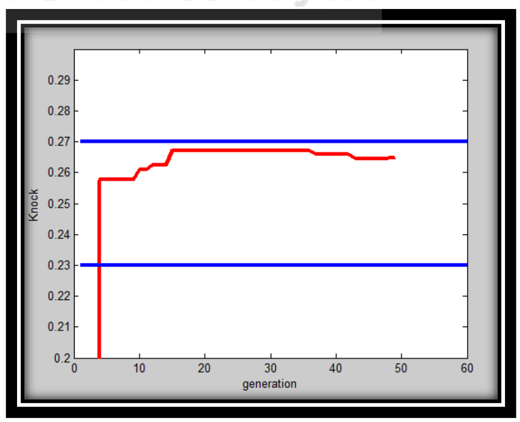
(3)


Knock
generation

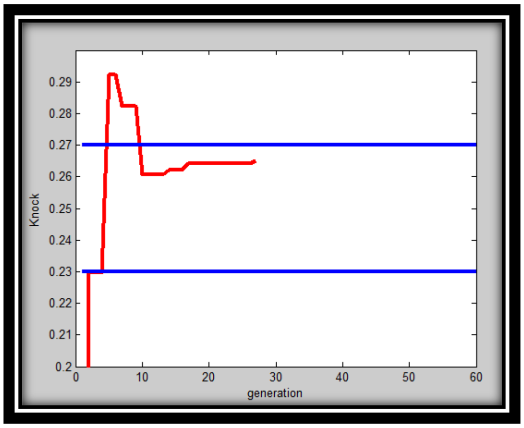
(4)


Knock
generation

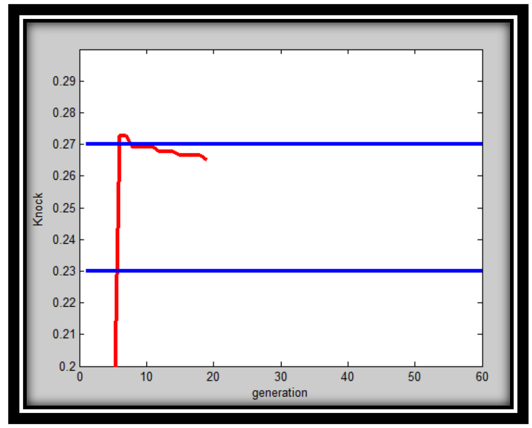
(5)


Knock
generation

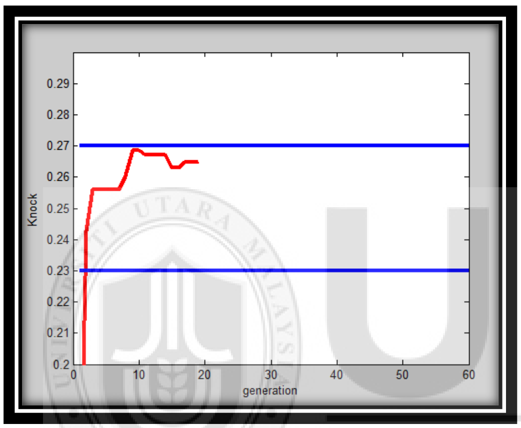
(6)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

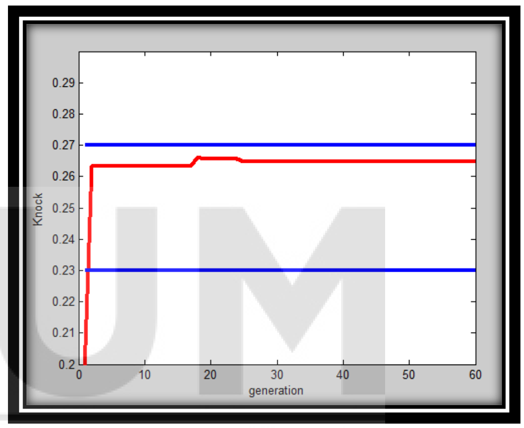
(7)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

(8)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

(9)


0.29
0.28
0.27
0.26
0.25
0.24
0.23
0.22
0.21
0.2
Knock
0
10
20
30
40
50
60
generation

(10)

APPENDIX E
DATA SETS

PROTON TURBO CHARGE

TPS	RPM	TEMP.	KNOCK
80.02320454129288	1000.5	90.1	0.27479553244339666
80.02182594762671	1000.4	89.9	0.3145224750739207
80.02204010507785	1000.3	90.1	0.3127932979287972
80.02101265030628	1000.5	90.3	0.32168359838959226
80.02027229444965	1000.4	89.3	0.34870855850050336
80.0210819446969	1000.4	90.3	0.34411675942900016
80.00625294512477	1000.5	90.6	0.292195760078057
80.00976142952834	1000.5	89.5	0.29028704089382235
80.01184026124425	1000.5	90.1	0.292558785175316
80.01235449856314	1000.4	89.9	0.31869671327074955
80.0123581456365	1000.4	89.8	0.31658149789903944
80.03112963132469	1999.9	90.0	0.17247724117107777
80.03151629223605	1999.8	90.3	0.17586395919059505
80.03051649428397	2000.0	90.2	0.1748822187824208
80.02979766144979	1999.8	90.2	0.18403744283795875
80.02973927908766	1999.9	89.8	0.18555168647629877
80.03167684373201	2000.0	90.1	0.1864885211388481
80.02031782539426	2999.8	90.3	0.40320785554277044
80.02346713056056	2999.9	90.1	0.39643188507843946
80.01904800901737	2999.9	89.5	0.4157507327499335
80.02087610673237	3000.0	90.3	0.47375244178007603
80.01998942460719	4001.0	90.0	0.6912158245182007
80.0198909043711	4001.0	89.8	0.7295861886218123
80.01836487517335	4001.0	90.2	0.7053926579266526
80.02004982298519	4999.6	90.4	0.7921056044720308
80.02011348712678	4999.5	90.1	0.8052391800473924
80.02067347250018	4999.5	89.9	0.8212442393102849
80.02113152956694	4999.5	89.9	0.8536828129098429

DODEG

TPS	RPM	TEMP.	KNOCK
2.6	740.0	50.0	0.5
2.8	745.0	50.0	0.6
2.9	750.0	50.0	0.7
3.0	780.0	50.0	0.8
3.1	790.0	52.0	0.8
3.6	800.0	53.0	0.9
2.5	850.0	55.0	0.6
2.5	950.0	55.0	0.6
3.0	960.0	56.0	0.8
3.1	980.0	57.0	0.7
3.2	990.0	57.0	0.7
3.0	1000.0	59.0	0.7
3.1	1050.0	60.0	0.7
3.1	1100.0	60.0	0.7
3.2	1200.0	60.0	0.9
3.2	1300.0	60.0	0.9
3.1	1350.0	61.0	0.8
3.5	1400.0	61.0	1.4
3.5	1470.0	64.0	1.5
5.0	1900.0	66.0	1.6
6.4	2000.0	66.0	1.7
9.1	2200.0	67.0	1.9
10.0	2400.0	68.0	2.0
12.0	2600.0	68.0	2.1
2.6	740.0	50.0	0.5
2.8	745.0	50.0	0.6
2.9	750.0	50.0	0.7
3.0	780.0	50.0	0.8

HYUNDAI-GENESIS

TPS	RPM	TEMP	KNOCK
0.4	541.0	87.0	-2.25
0.4	543.0	96.0	-2.25
0.4	546.0	90.0	-2.25
0.4	550.0	93.8	-2.25
0.4	552.0	88.5	-2.25
0.8	583.0	92.3	-2.25
0.8	588.0	93.3	-2.25
0.4	589.0	90.8	-2.25
0.4	595.0	91.5	-2.25
0.8	595.0	90.0	-2.25
0.8	629.0	90.8	-2.25
0.8	636.0	92.3	-2.25
1.2	699.0	91.5	-2.25
1.2	739.0	94.5	-2.25
0.8	742.0	91.5	-2.25
0.8	759.0	91.5	-2.25
1.6	856.0	90.8	-2.25
1.2	878.0	94.5	-2.25
1.2	893.0	93.0	-2.25
1.5	933.0	93.0	-2.25
1.2	950.0	91.5	-2.25
1.6	1027.0	93.0	-2.25
1.6	1043.0	93.0	-2.25
2.4	1321.0	91.5	-2.25
2.4	1329.0	95.3	-2.25
2.4	1341.0	96.0	-2.25
3.5	1646.0	93.8	-2.25
3.5	1688.0	93.8	-2.25
5.5	2316.0	92.3	-2.25
5.9	2514.0	93.0	-2.25
7.8	3156.0	92.3	-2.25
0.8	759.0	91.5	-2.25

KIA MOTORS-SORENTO

TPS	RPM	TEMP.	KNOCK
1.3	665.0	92.0	0.0
1.38	670.0	91.0	0.0
1.44	675.0	90.8	0.0
1.74	689.0	89.3	0.0
1.74	695.0	89.7	0.0
1.74	705.0	90.0	0.0
1.79	720.0	90.0	0.0
1.9	736.0	90.0	0.0
2.2	745.0	90.0	0.0
2.5	850.0	90.2	0.0
2.9	940.0	90.4	0.0
3.5	1150.0	90.5	0.0
4.63	1576.0	90.8	0.0
4.6	1585.0	91.0	0.0
4.45	1630.0	92.0	0.0
4.35	1725.0	92.5	0.0
4.22	1896.0	93.0	0.0
4.22	1907.0	92.3	0.0
4.22	1915.0	91.5	0.0
4.28	1940.0	91.5	0.0
4.34	1975.0	92.0	0.0
4.5	1975.0	92.5	0.0
4.7	2035.0	92.0	0.0
5.0	2189.0	93.0	0.0
5.26	2240.0	94.0	0.0
5.87	2604.0	95.3	0.0
5.87	2616.0	94.5	0.0
6.4	2870.0	92.0	0.0
8.03	3417.0	90.0	0.0
8.13	3473.0	90.0	0.0