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

AZHER RAZZAQ HADI WITWIT



**DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
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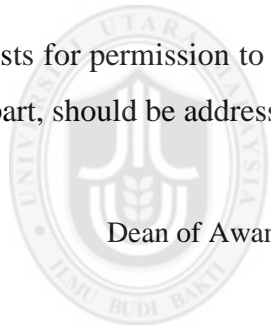
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Abstrak

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 wajar 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 Agregat Bukan-Wajaran (NWAEF) untuk bukan linear fungsi multi-objektif yang akan meniru tingkah laku ketukan enjin (pembalahubah bersandar bukan linear) untuk mengoptimumkan keputusan faktor bukan linear (pembalahubah bebas bukan linear). Kajian ini telah memberi tumpuan kepada pembinaan satu model NWAEF dengan menggunakan keluk 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, Algoritma 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 propose 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

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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}	$N_{\text{gene}} * N_{\text{par.}}$: 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

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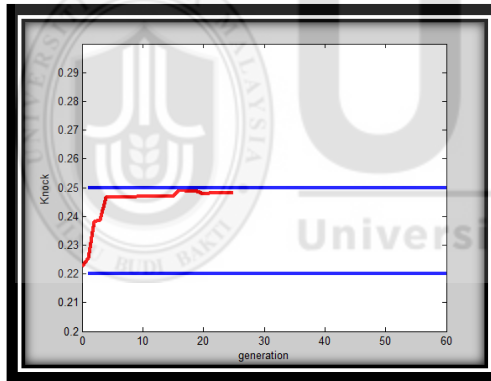
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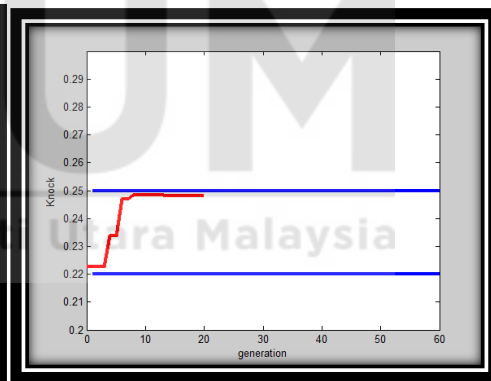
APPENDIX A

PROTON_TURBO CHARGE ENGINE

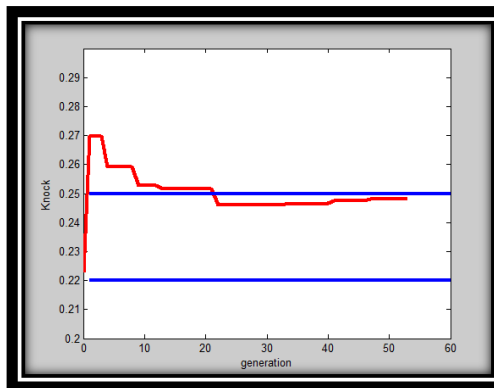
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.030314	25	0.24803	80.013	1218.1	89.905
2	0.033244	20	0.24802	80.023	1199.9	90.135
3	0.042071	53	0.24799	80.021	1205.5	91.364
4	0.053894	60	0.24721	80.012	1215.4	91.382
5	0.041634	60	0.24836	80.345	1195.7	90.504
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



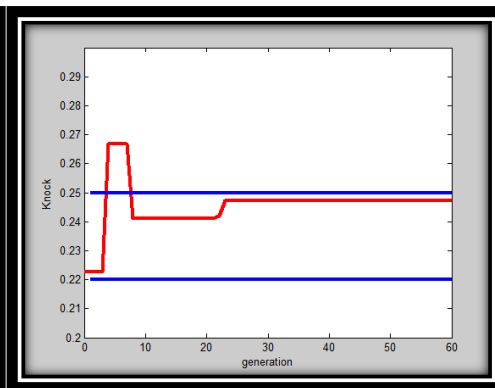
(1)



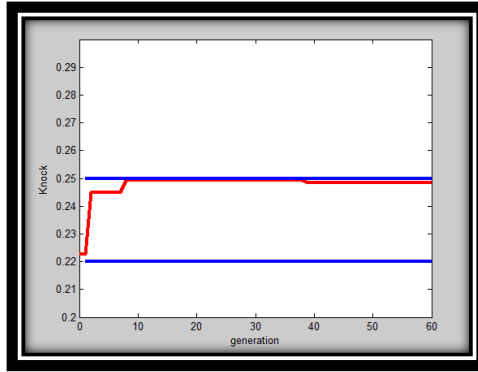
(2)



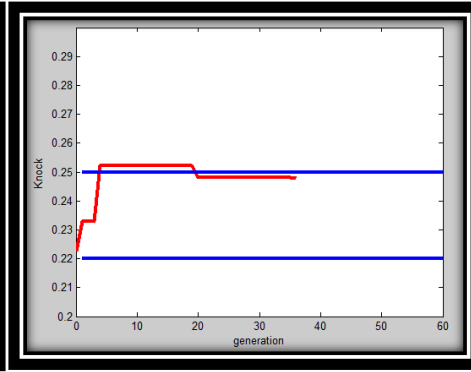
(2)



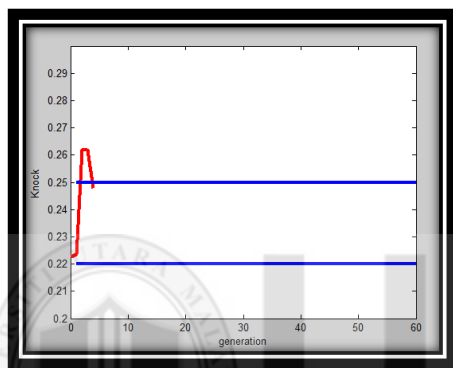
(4)



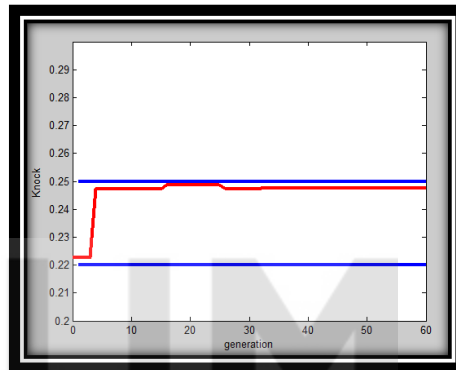
(5)



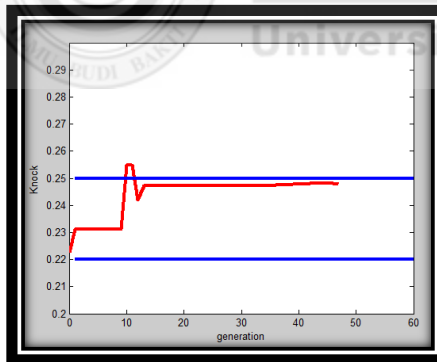
(6)



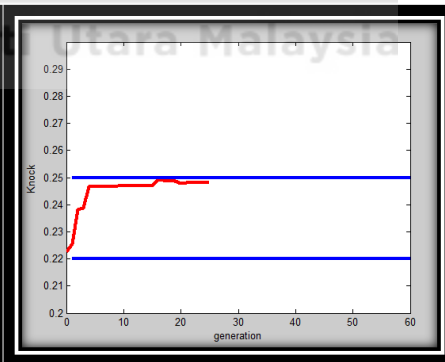
(7)



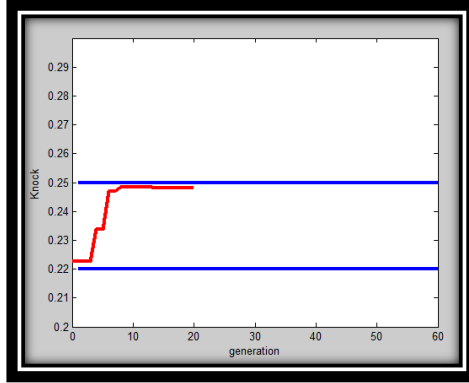
(8)



(9)



(10)

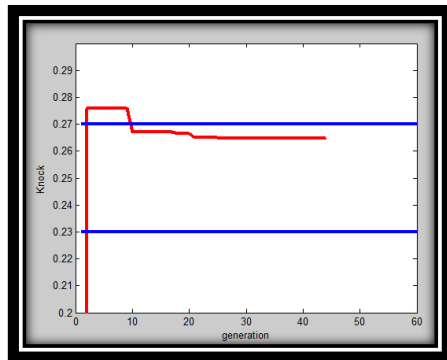


(11)

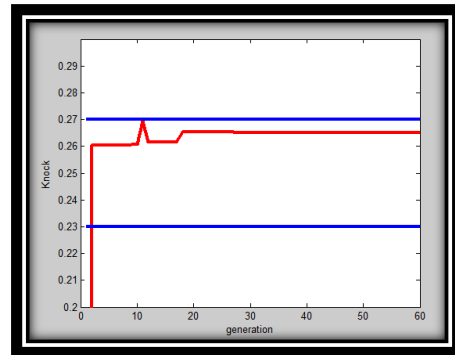
Appendix B

KIA_Motors_Sorento

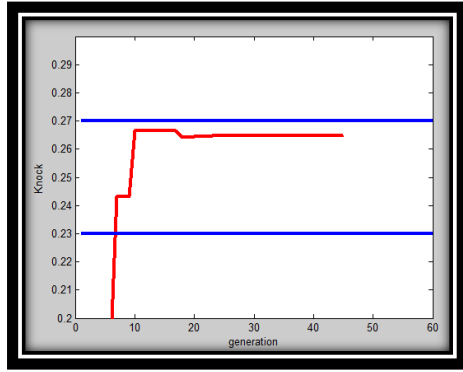
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.046865	44	0.26499	7.6713	1717.5	91.582
2	0.054338	60	0.26514	7.562	2032.3	92.55
3	0.040090	45	0.26494	7.4681	2397.3	89.915
4	0.036770	43	0.26498	7.4644	2416.2	91.174
5	0.061880	54	0.26499	7.4904	2302.2	90.591
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



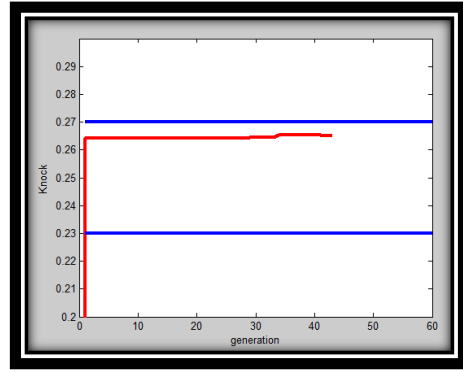
(1)



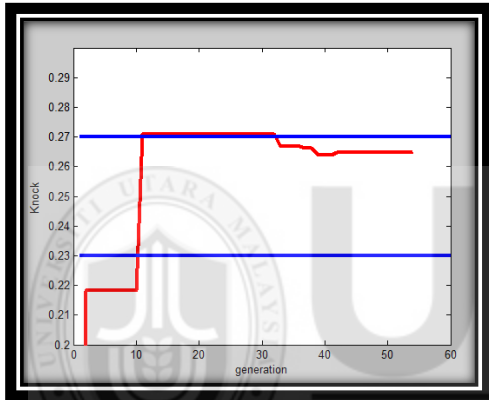
(2)



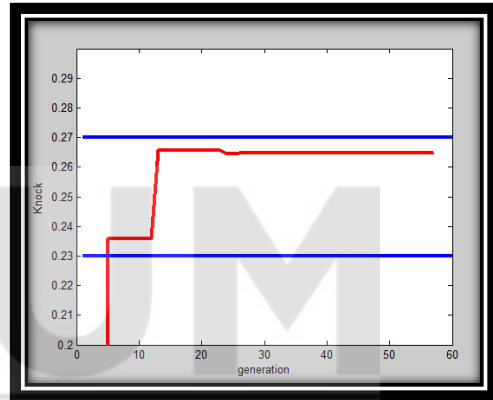
(3)



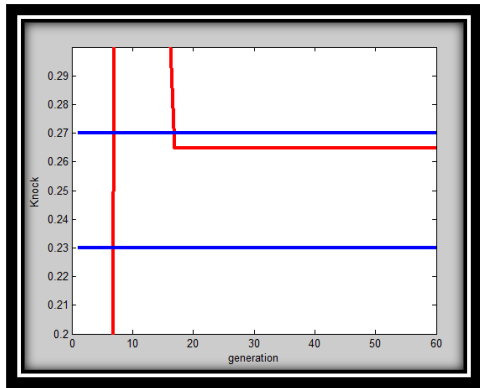
(4)



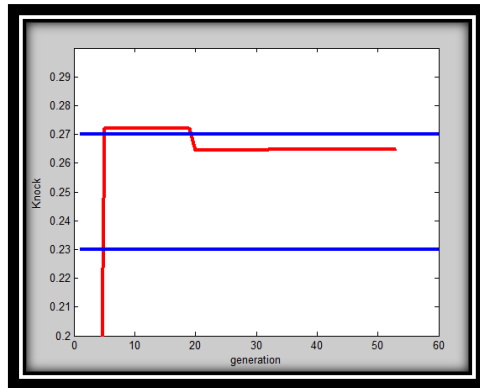
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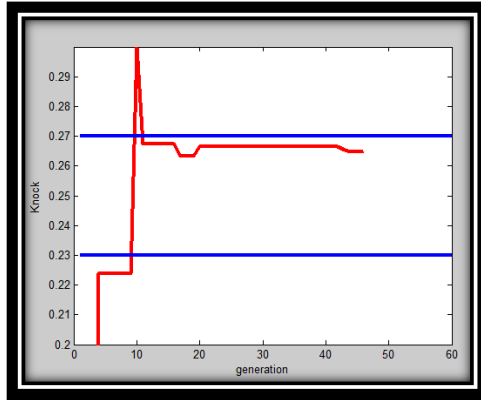
(6)



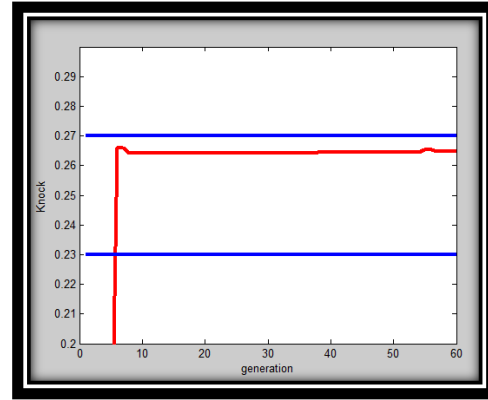
(7)



(8)



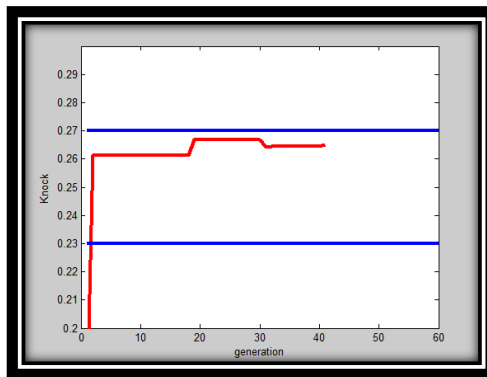
(9)



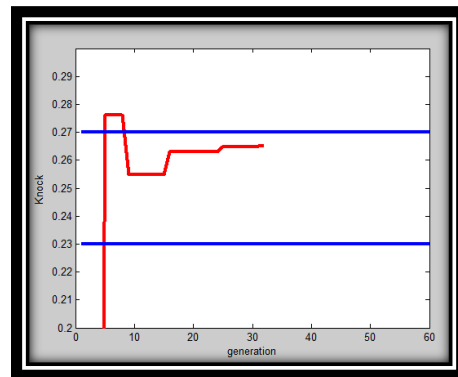
(10)

Appendix C Hyundai_Genesis Engine

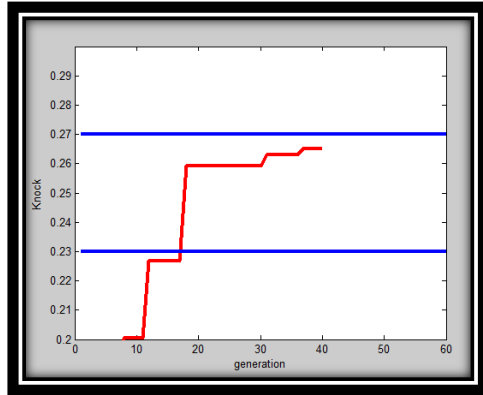
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.041626	41	0.26504	7.6469	1776.1	91.387
2	0.032792	32	0.26498	7.6585	1753.9	95.858
3	0.046630	40	0.26494	7.5212	2180.6	92.85
4	0.043320	59	0.26507	7.4781	2355.7	90.784
5	0.028497	25	0.26498	7.4744	2372.4	91.715
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



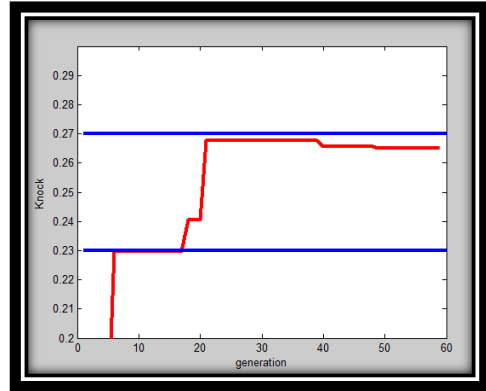
(1)



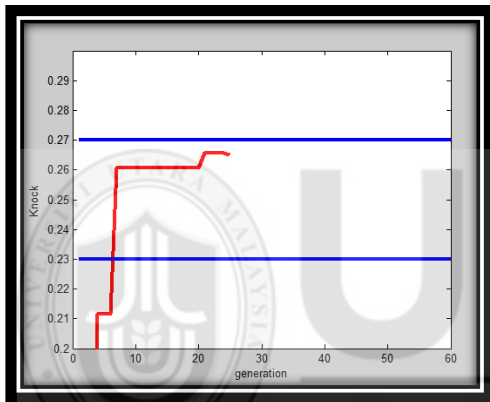
(2)



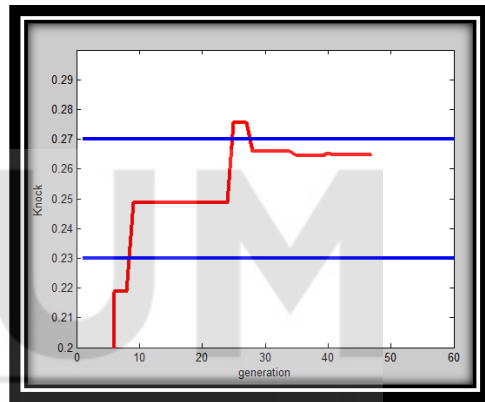
(3)



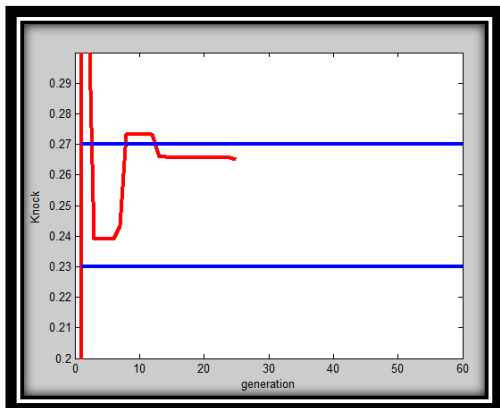
(4)



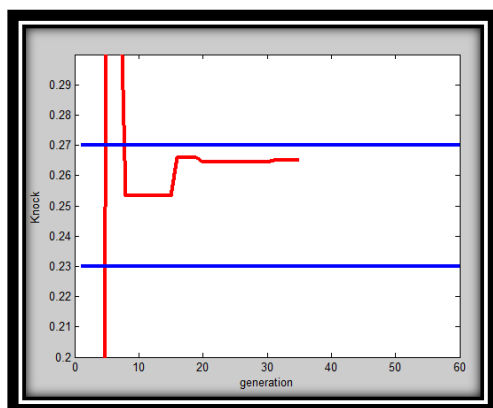
(5)



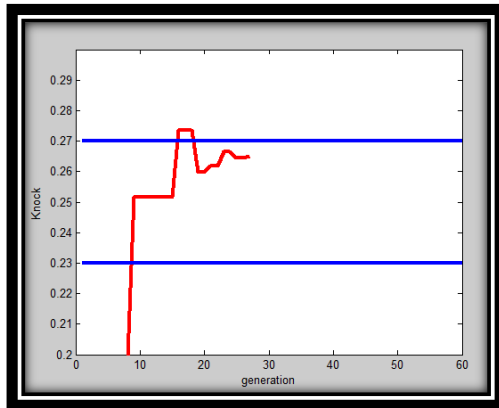
(6)



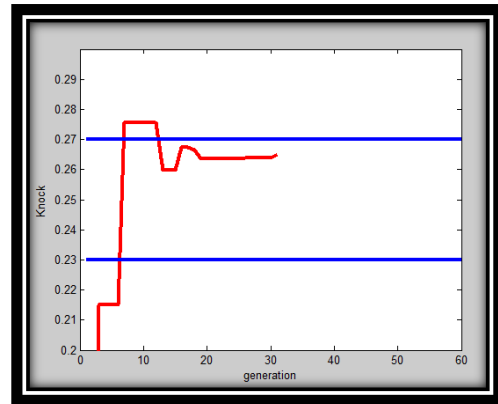
(7)



(8)



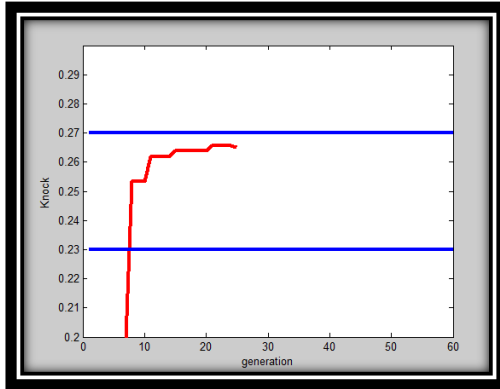
(9)



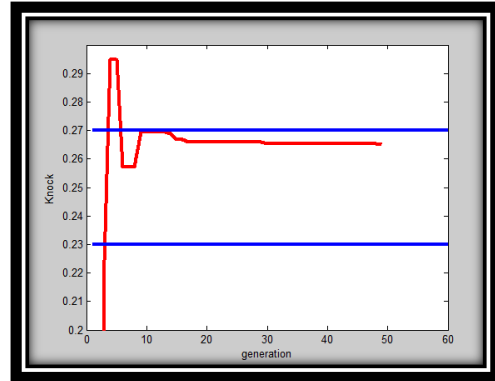
(10)

Appendix D Dodeg Engine

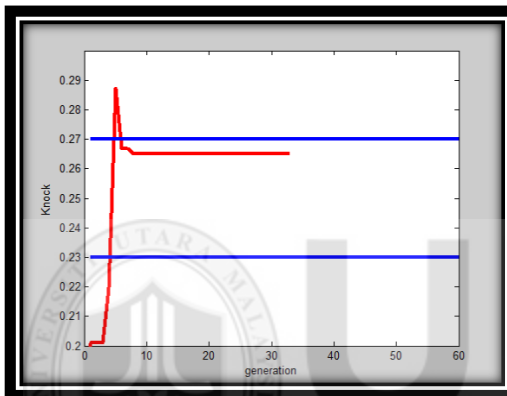
RUN	Elapsed time	Generations	Best Knock	Optimal Factors(Best solution)		
				TPS	RPM	TEMP.
1	0.036748	25	0.26496	7.8568	1482.4	53.379
2	0.050063	49	0.26494	7.5149	2199.8	60.493
3	0.035558	33	0.26507	7.5659	2012.9	58.467
4	0.049124	34	0.265	7.7616	1559.9	66.594
5	0.078471	60	0.26447	7.6748	1701.7	58.603
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



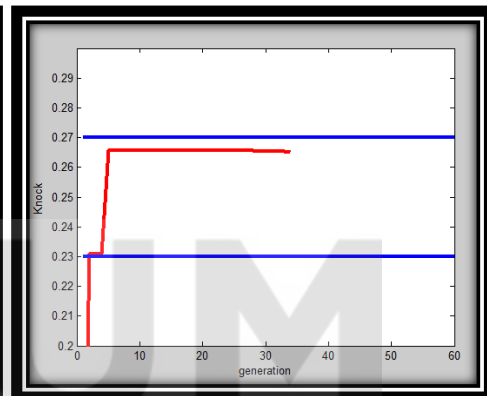
(1)



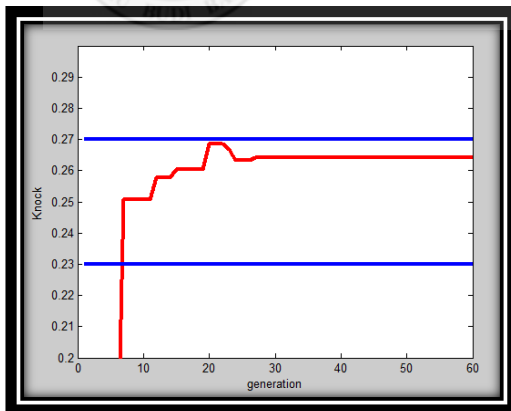
(2)



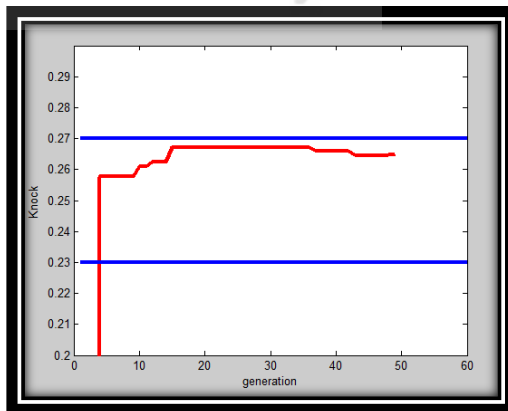
(3)



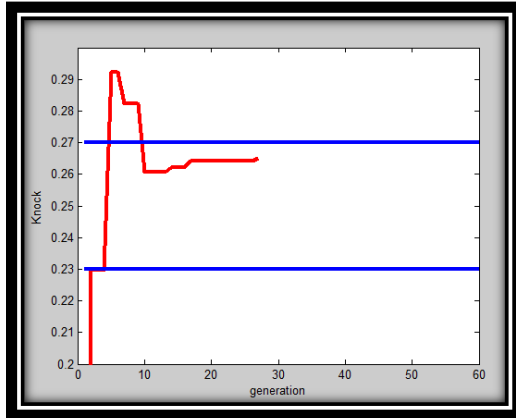
(4)



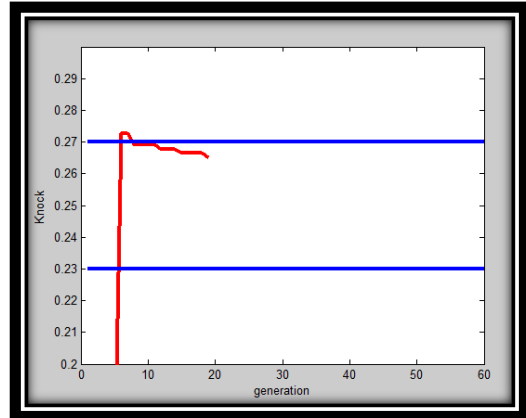
(5)



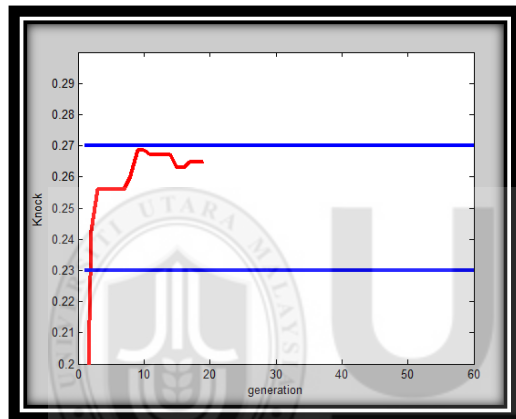
(6)



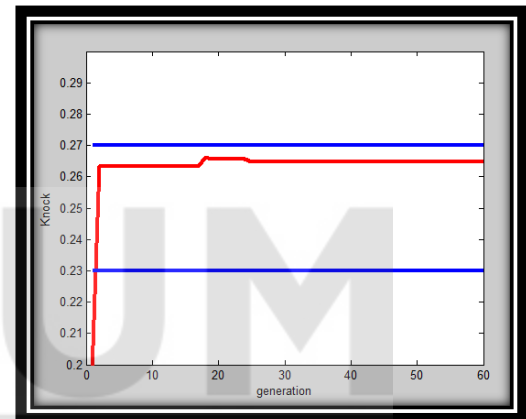
(7)



(8)



(9)



(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