International Journal of Engineering Science Invention
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 6 Issue 5|| May 2017 || PP. 71-78

Optimizing ElectricalPower with Artificial Neural Networks and Genetic Algorithm

Satya Sobhan Panigrahi[1], Geetidarshini Panigrahi[2], Sujit Panda[3]
[1,3]Associate Professor, Department of Computer Science Engineering, Gandhi Institute For Technology (GIFT), Bhubaneswar
[2]Assistant Professor, Department of Computer Science Engineering, Gandhi Engineering College, Bhubaneswar

Abstract: *In this paper the power consumption of an A.C. inductionmotor wasoptimized. Toachievethis,variousparametersofmotorand outputs were obtained through tests .by using artificial neural network, the relations between input and output parameters were determined. Subsequently, for obtaining the minimum energy consumption with the maximum output, the parameters were optimized in three cases of maximum load, without load and average load (50% of the load capacity) using the genetic algorithm. Finally, the input parameters optimized values were entered into the trained model and optimized power valueswere calculated.Theobtainedvaluesweretestedinpracticeinallthree casesanditwasobservedthatthepresentedmethodcouldpredict the optimized power for three cases of maximum load, without load and average load with 4.5% ofaccuracy.*

Keywords: *ElectricalMotor-NeuralNetwork-GeneticAlgorithm-Optimization -Power Consumption*

I. Introduction

Applicationofelectricalmotorsforaccuratesystemsisincreasing day by day in the present world. Considering the competitive conditions, designing systems which consume minimumenergy and have maximum outputseemstobeofsignificance.Sinceproducingandtestingsuchmotorsarecostly,usingmethodswhichconsumeminimumtimeandcostsarebeingconsidered.byusingartificialneuralnetworksandgeneticalgorithm.electricalmotorsareoneofthemostcommontorquesystemsforvarioussystems,becausetheycanachievehightorqueinaverycompactsize,theyareeasytocontrolandtheyareverylowinnoiseandairpollution.

A.C.Electricalmotorsaremostusedforindustrialcontrolsystems and also some home appliances. The mainbeneficialpointsoftheseElectricalmotorsarethereSimpleandtenaciousdesign,lowcost,lowmaintenancecostandalsotheyuseafullconnectiontopowersupplysimply.Butinsomecasesbecausetheirhighlevelofenergyconsumption,theyarenotsopopular.Oneofthebasic issues is the high current intake in the rudiment torque gaining period,whichisdirectlyrelevanttotheElectricalmotor'senergy consumption.

Tosolvesuchproblems,therelationshipbetweennonlinearparametersandthereeffectsshouldbeclearlydetected.defining theeffectofeffectiveparametersinpowerconsumptionandtorque by taking advantage of the Neural Networks, due to their ability inmodelingofcomplexprocesses,isstronglyrecommended.But sometimes these neural networks may be a little hard to use and maynotbeeconomical,duetothehugeamountofdataneededto trainingandtestingofneuralnetworks.Inmostsituationsthateven analytical methods are not able to build relevant models,neuralnetworkwillbebeneficial.determiningtheregulatoryparametersfortakingthelowestenergyiscrucialinordertohaveElectrical motor'swithmaximumpoweroutput.Usingthegeneticalgorithm to optimize these parameters, suits the situation because it hasaverysimplestructureanditisusefulforcalculatingtheoptimum outcome. There have been lots of research activities in the field ofoptimizingElectricalmotorsparameters.ForexampleBagden Pryymaketal.[1]minimizedtheenergywastagebyconsidering the speed and torque. M. W. Turner et al. [2] have optimizedthe energyconsumptionofanElectricalmotorby20%,onlybyusing a phase logic based system, as a result they have shown that the electrialmotor'senergyintakehasbeenreducedinto80%ofwhat was taken earlier, and the shaft rotation speed was controlledby0.5 RPM deviation.

A.Betkaetal.[3]haveoptimizedaphotovoltaicpump,whichuses a 3-phase Electrical motor, only by utilizing SQP(a non-linear algorithm) and Matlab software. MR. Seydi Vakkas Ustun et al. [4], optimize the Electrical motor by 15% of the nominalpower, bytakingadvantageofthegeneticalgorithm.MR.Spiegelaetal. [5], showed the usage of the Expert systems in accordance with Electricalmotor.MR.FangLinLouetal[6],haveresearchedthe effective parameters in Electrical motor's energy consumption. Inmostcases,theusedtoolswerecomplexandtheeffectsoftwo close parameters (like motor's controllingvoltageandconstantvoltage)werenotofmuchconsideration.Regardingthispoint,inthisarticle,controllable A.CElectricalmotorenergyconsumption optimizedbyvoltagebyaNeuralnetworkandGeneticAlgorithm. To do so, different levels of input data were calculated, and a combination of inputs were programmed with regard to the two levels of no-load and full-load network, and with the help of trained network the output level of energy was defined.Besidethat,thelevelofmediumloadenergywascalculatedwiththehelpoftrainednetwork,anditwaspracticallytested,andintheendtheinputparameterswereoptimizedforthreestatesofLow,Mediumandfullloadbythehelpofgeneticalgorithm.Theresultedvalues wereenteredintothetrainednetworkandtheresultedpowerlevels were also tested practically and the tolerance wascalculated.

II. Experimentation

Inthepresentresearchwork,thegoalistodeterminetheoptimum values for three following parameters, Constant voltage(V1),Controllingvoltage(V2)andtheload,withthehelpoftoolssuchasexperimentsdesign[11],Neuralnetwork[12-13]andGenetic Algorithm [14], so that the motor's power consumption is inthe optimum mode. In this paper a Neural network is designed for forecastingtherelationshipbetweenthethreeinputparametersand consumedenergy.AndconsidertheGeneticAlgorithmapplicationinoptimizationofpower.Inthispaper,theexperiments weredonein5constantvoltagelevels,7controllingvoltagelevels,andtwooutputlevelofthepower(noloadandfullload),constantcurrent andcontrollingcurrentwascalculated.Tomeasuretheconsumed power, a wattmeter was used. This wattmeter is connected to a power source which is the main source for the three input parameters, and calculates the power by measuring the input voltage and current.TheexperimentwasconductedonanA.C.Electricalmotor.Notethattheloadvalue0,0.5,1isrepresentingtheElectricalmotor's mechanical torque capacity usage. When zero, the torque value is0,when1,thetorquelevelismaximumandwhenthisvalueis0.5thetorquelevelis50%ofElectricalmotor'storquecapacity. Theimportantinputparameterswhicharementionedinthispaper are listed in table 1. This motor is a two-phase Electrical motor, whichcontrollingdiagramisrepresentedinfig.1.Infact,atwo- phase Electrical motor is a servomotor. These types of motors are used in computers, CNC systems and any other instruments whichneedhighaccuracy.Theoutputpowerofsuchmotorscan be in a range of 2 watts to hundreds of watts. bigger motors in terms of power are usually have very low revenue, if they were not made by Appropriate torque and speed characteristic it will betroublesomeinservomotoruses.Asisshowninfigure1these motorshaveaconstantleveloftorqueinallrotationspeeds.Indeed one of the preferences for such motors is their manageability in low speeds. So in order to have a constant torque in a specific rotationspeed,theconsumedpowershouldbevaryinginaspecific range, and since high accuracy is very important, the consumed power in servomotors in both rudiment and no-load statesare of a great importance.

Table 1: Different Input Values

Load	Fix Voltage	Control Voltage	Voltagelevel
0	115	5	Level 1
1	100	10	Level 2
-	85	15	Level 3
-	70	20	Level 4
-	55	25	Level 5
-	-	30	Level 6
-	-	35	Level 7

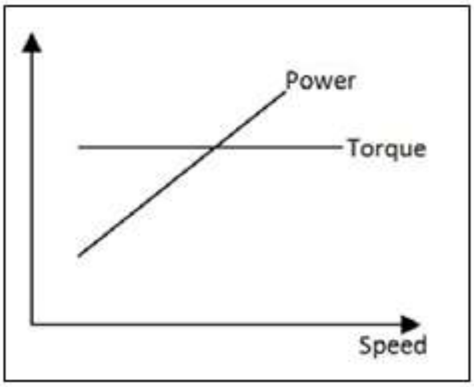

Fig. 1: Torque and Power Figure by Speed [17]

III. Design of Experiments

An optimum experiment should lead into desired optimum state with the least number of tests, data, and information which is needed. One of the methods which is taken in this experimentis the“FactorialExperiment”.InthespecifiedElectricalmotor,the constant voltage will be floating in a range of 0 to 115 volts and the controlling voltage will be varying from 0 to 35volts. Inordertoobtaintheproperrelationshipbetweentheseparametersthewholerangeshouldbechecked.Whentheexperiment conductedinapracticalmanner,itwasnoticedthatthecontrollingvoltagesbelow4voltshasnoeffectontheprocessofmotorcontrolandfor the voltages upper than the 5 volts it’s effect is clearly sensible. in the constant voltages below 53 voltstheoutputtorquewouldhardlyslump.Theotherobviousconsequenceistheeffectofchangingthesetwovoltageswhichiswhenthereisasmallshift in controlling voltage, there is a noticeable change in motor’s consumed energy, but for the constant voltage this happens in a larger range. In order to check the effect of the whole domain, controlvoltagevaryintherangeof5-35bythestepof5voltsand constant voltage vary in the range of 55-115 volts by the step of 15volts.byusingthefactorialexperiment,thenumberofrequired tests for considering all the input effect, including 5 levels of constantvoltage,7levelsofcontrolvoltage,and2levelsofload amplitude, were totally resulted in 70 levels, shown in Table2.

Table 2: DC Motor Test Results in Saturation Mode

test	load	v1	v2	speed	torque	P total
1	0	115	5	7110	0	44.5
2	0	100	5	7130	0	31.2
3	0	85	5	7112	0	21
4	0	70	5	7058	0	13.5
5	1	115	5	0	0.109	68.7
6	1	100	5	0	0.087	46
7	1	85	5	0	0.069	30.1
8	1	70	5	0	0.051	18.9
9	0	55	5	6901	0	8.5
10	0	115	10	7529	0	35.7
11	0	100	10	7549	0	24.5
12	0	85	10	7574	0	15.7
13	1	115	10	0	0.253	73.1
14	1	100	10	0	0.207	50.1
15	1	85	10	0	0.165	34
16	1	70	10	0	0.126	22.5
17	1	55	10	0	0.09	14.7
18	0	70	10	7582	0	10.3
19	0	55	10	7536	0	7
20	0	115	15	7715	0	29.1
21	0	100	15	7749	0	18.4
22	0	85	15	7767	0	13
23	1	115	15	0	0.406	81.1
24	1	100	15	0	0.326	57.7
25	1	85	15	0	0.258	41.2
26	1	70	15	0	0.198	29.6
27	0	70	15	7768	0	9.4
28	0	55	15	7723	0	7.6
29	0	115	20	7829	0	22.9
30	0	100	20	7854	0	16.7
31	1	55	15	0	0.143	21.4
32	1	115	20	0	0.576	93.6
33	1	100	20	0	0.469	69.8
34	1	85	20	0	0.376	53
35	1	70	20	0	0.287	40.9
36	0	85	20	7860	0	12.7
37	0	70	20	7839	0	10.9
38	0	55	20	7783	0	10.4

39	0	115	25	7895	0	22.6
40	0	100	25	7898	0	17.9
41	1	55	20	0	0.211	32.5
42	1	115	25	0	0.756	112.3
43	1	100	25	0	0.619	88.2
44	1	85	25	0	0.495	70.8
45	1	70	25	0	0.384	58.2
46	0	85	25	7892	0	16.1
47	0	70	25	7857	0	15.8
48	0	55	25	7769	0	17
49	0	115	30	7922	0	26.6
50	1	55	25	0	0.284	49.5
51	1	115	30	0	0.95	139.6
52	1	100	30	0	0.781	113.7
53	1	85	30	0	0.626	95.8
54	1	70	30	0	0.486	82.7
55	0	100	30	7912	0	23.3
56	0	85	30	7885	0	22.6
57	0	70	30	7826	0	25.4
58	0	55	30	7728	0	30.8
59	0	55	35	7669	0	50
60	1	55	30	0	0.362	73.4
61	1	115	35	0	1.166	179.1
62	1	100	35	0	0.958	151
63	1	85	35	0	0.768	131.4
64	0	115	35	7927	0	38.3
65	1	55	35	0	0.448	107.6
66	0	100	35	7912	0	34.5
67	1	70	35	0	0.602	117.5
68	0	85	35	7861	0	39.6
69	1	55	5	0	0.04	10.9
70	0	70	35	7787	0	44.8

IV. Modeling

In this research for the specified designed motor, the consumed power is optimized by the input parameters.Fordefiningthecomplexrelationshipoftheseinputparametersan ArtificialNeuralNetworkhasbeenused.AnArtificialNeuralNetwork(ANN)isaninformationprocessingparadigmthatisinspiredbythebiologicalnervoussystems,suchasthebrain,processinformation.Inordertodesignthisneuralnetwork,theQnetsoftwarewasused.Toobtainthebestneuralnetworkmodel,differentlayerswithdifferentnodeswere simulatedandwereassessedandintheendanetworkwiththeleasterrorswasresulted.Thespecificationsofthisnetworkareasfollow,3inputs,2hiddenlayerswith10neuronsinfirsthidden layer and 7 neurons in second hidden layer and on output layerwith1neuron.ThisNeuralnetworkmodelisshowninfig.2,outof70testswereconductedtotrainthenetworkandtheother7test were conducted for testing the network and comparing obtained result with the practical result. Finally the network was trained by the threshold level of 0.5 and the training random rate with Square root error of 0.000962. The dispersal of the trainingdata was with the overlap value of 99.98% , is shown in fig. 4. The trained model was tested with just 10% of the real data and the tolerancewas0.026.Thedispersalofthetestdataisshowninfig. 5. The compatibility of the test data and the main data is shown infig.6.Withregardtothetest'serrorandfigs.5and6,wecometothispointthatthenetworkisabletoforecasttheoutputpowerbytakingtheinputregulatoryparametersintoconsideration.Themostnoticeablepointofdesignedneuralnetworkisit's abilitytodefinethecomplexandnonlinearrelationshipbetweenthemotor'sconsumedpowerandit'sparameterswhichincreasesthemotor's outcomeanddecreasesit'spowerwastage.Intheend,thistrained model was used to measure the output power level in load state of0.5andassesstheoptimumdatawiththehelpofusedgenetic algorithm.Theoutputpowerinaverageloadwith Averagerelative error of 8.5% with the help of trained model wasobtain.

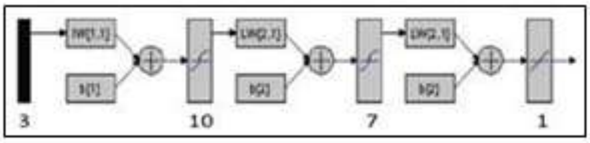

Fig. 2: The Programmed Neural Network Model Optimization

A. AeneticAlgorithm

The theoretical foundations for genetic algorithms were first described by John Holland [18] and then presented tutorally by David Goldberg [19]. Genetic algorithms are search algorithms basedontheprocessofbiologicalevolution.Geneticalgorithmisastochasticsearchmethodbasedongeneticconceptsthat isusedtosolvetheoptimizationproblemtoachieveoptimalsolutionorasolutionclosetothatoptimalsolution.Inanoptimizationproblemthatitsoptimizationparametersare.Atfirst,somegeneralpoints within the range which called population are selectedrandomly, andthenthesepointsarecoded.Usuallythecodeboxesareformed by from 0 and 1. Fig. 3, displays optimal solution by genetic algorithm for a hypothetical problem in which the population consists of four code box. These boxes are calledchromosomes. Each chromosome, is a volunteer to solve the optimum value. Chromosome growth should be in the direction that results in an optimal solution for the problem. For the next chromosomes producing, each chromosome is evaluated in the function value. Each of these chromosomes which have higher function values aremorevaluable.Theprobabilityofeachchromosomeselected for reproduction depends on the function value. For example, in fig. 3, function value of each chromosome is equal to the number of 1s in the box. For each pair of parents from selective chromosomes, two infants are created by basic operator namely crossover[20].Crossoverfromsingle-pointaredifferentfromthe other crossovers. in a single- point crossovers, a crossover point is selected randomly, then from the starting point, binary codes to the crossover point are carried from parent to parent and vice versa. And in the next step (i.e, Mutation) a bit of chromosome is reversed. Then these process continue and optimization are done [21].

	Fitness value	**Chance of being selected**							**Fitness value**
1100110	0.4	30.77%	1010001			1010000		1010100	0.3
1010001	0.3		1100110			1100111		1110111	0.6
0100100	0.2		0101011		**Croer sso v**	1101011	**Mutn atio**	1101001	0.4
0101011	0.4 77%	30.	1100110			0100110		1100110	0.4
Generation								**Generation**	

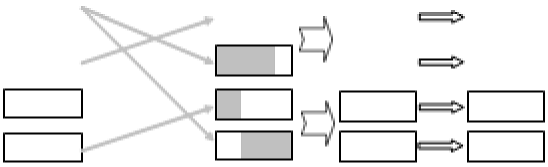

Fig. 3. Schematic Genetic Algorithms to Solve a Hypothetical Problem

B. ObjectFunction

The genetic algorithm toolbox of matlab7 software was usedfor optimization. The firststepistodefinetheobjectivefunction.In this paper, the P which is include four variables, is considered as the objective function. inimtab14 has been used to define the P function. To do so the numbers have been normalized. So, the objective function with 97% of regression is shown asbelow:

$$p = -0.0996 + 0.393 \cdot i^2 + 2.38 \cdot i - 0.257 \cdot (\text{load}) - 1.88 \cdot (v_1)^2 + 0.736 \cdot (v_1)^3 + 4.71 \cdot (v_2)^2 + .01 \cdot (v_2)^3 \tag{1}$$

C. Conditions

Here,theconstantcurrent(i)istakenastheoutput,whichisnotaregulatoryitem.soinordertopreventthiscurrentfromexceeding it'slimits,formula2isdeterminedasacondition.Thisformulais defined with the help of Minitab14 with the 96% ofoverlap

$$-I_1 - 0.294 + 0.97\,V_1 - 0.68\,V_1^2 + 0.60\,V_1^3 + 0.268\,(load) - 0.54\,V_2 + 0.19\,V_2^2 + 2.7\,V_2^3 \geq 0 \qquad (2)$$

In formula 1 and 2, P is the output power by watt, V1 is the constantvoltagebyvolt,V2isthecontrollingvoltagebyvolt,IisthecontrollingcurrentbyampereandLoadistheusagecapacity of the mechanical torque of motor. Because of the limitations which are exist in regulatory parameters, conditions for V1 and V2are,55≤V1≤115and4≤V2≤35.theoptimizationprocesswas performed in three stages by considering of objective function andconditionsinthematlabgeneticalgorithmtoolbox.Firststage for no-load state, second stage is for full-load state and the third stage is for half-load state, shown in table 3. in each three states theoptimizedvalueobtainafterfivegeneration.Fig.7,showsthenumberofgenerationsaccordingtoconvergenceoftheobjective function in load 0.5. As is shown in table 3, the optimum power level occurs in 115v of constant voltage inall3statewhichiscompletelyreasonableaccordingtothemotor'svoltage(motor'svoltageis115v).Thebestcontrolling voltagetoobtainthepoweroutputinnoloadstateis23.11465v,forfullloadstateitis5.0036v, in half-load it is10.0096v.

As it is noted, as the motor's capacity rises, the optimum power occursinalowerlevelofcontrolvoltage,andthisvoltagereaches it'sminimumandisequalto5.0036v.Attheend,theseobtained optimum values were put through the simulated model and the optimumpoweriscalculated.Theobtainedresultsfromsimulated model were practically tested and they were compatible with a 4.5% of average tolerance, shown in table 4. This highaccuracy levelshowstheabilityofthismethodforforecastingtheoptimum level of power for A.C. Electrical motors which arecontrollable by regulatory voltage inputs.

Table 3: Optimum Values in Accordance with the Inputs from Genetic Algorithm

load	Current(ampere)	Controling voltage(volt)	Constant voltage(volt)
0	0.8692	23.1146	115
1	1.345	5.0036	115
0.5	1.091	10.0096	115

Table 4: The Comparison Between Real and Optimum Values

Optimum parameters			Network output	Real output	Error percentage
$V_{1(v)}$	$V_{2(v)}$	load			
115	23.1146	0	22.53	21.5	4.6
115	5.0036	1	69.3	68.7	0.9
115	10.0096	0.5	48.92745	45	8

VI. Conclusion

In this paper 70 practical tests were conducted on inductional motorwhichisincludecombinationofthreeparameters,constantvoltage,variablevoltage(controlingvoltage)andloadingcapacity as inputs and consumed power as an output. With 90 percent of the data of an artificial neural networkwith3*10*7*1structureandaccuracyof0.000962wastrainedandwiththerest10percentofthedatathisnetwork wastestedwiththeaccuracyof0.026.Withthehelpofthetrainedmodelthepowerlevelin50%ofload was determined with 8.5% ofaccuracy.Aftertrainingofnetworkandobtainingofobjectivefunction,the conditions were included in genetic algorithm, and theoptimum power level was calculated for no-load, half-load and full-load states.Toconfirmtheresults,theobtainedvalueswereputthrough the trained model and optimum power level was calculatedforthese3loadstates.Afterthesepracticaltestswereconducted,theinputparametersshowninTable3,therealvalueswerecalculated and were shown with their tolerance in Table4.

Theaverageoptimizingtolerancesinall3statesareequalto4.5%, which is totally reasonable and suitable for measured consumed powerofelectricalmotor.Theresultsshowedthatthesemethods (artificial neural network and genetic algorithm) are very useful toolsforforecastingtheoptimizedpowerlevelinA.CElectrical motors with controllable voltageinputs.

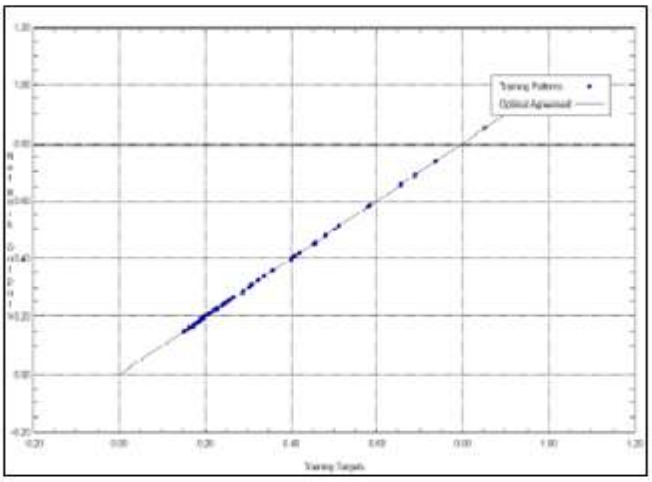

Fig. 4: Dispersal of Program Data

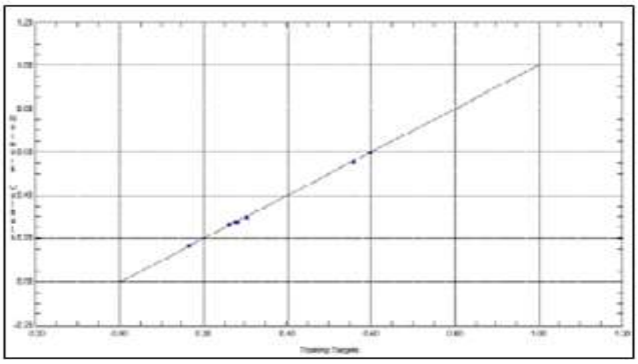

Fig. 5: Dispersal of Test Data

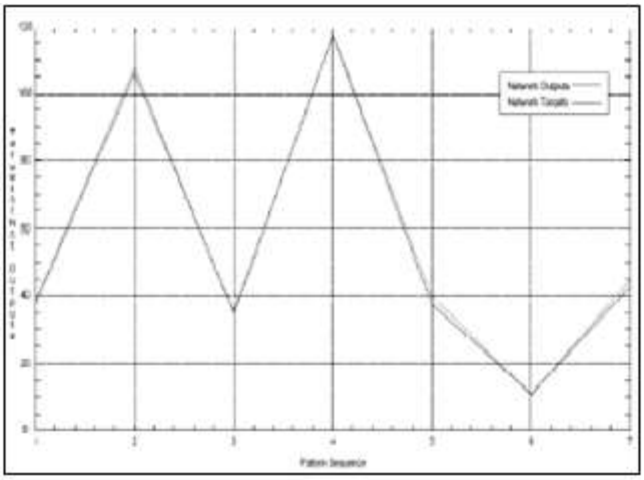

Fig. 6: The Test Data and the Main Data Compatibility Value

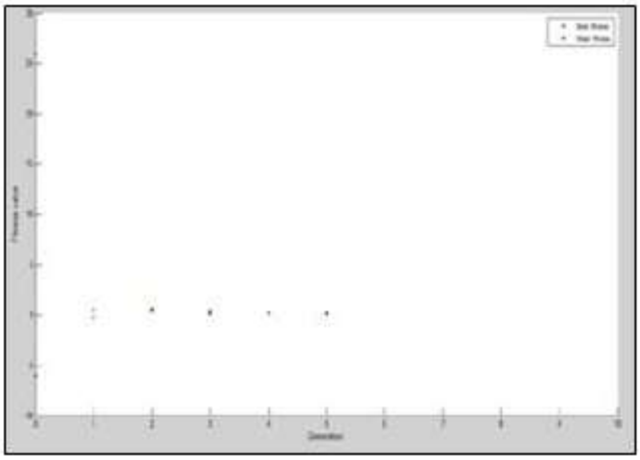

Fig. 7: Function’s Value Convergence Based on Generations Numbers

References

[1]. Bogdan Pryymak, Juan M. Moreno-Eguilaz, Juan Peracaula,“ Neuralnetwork flux optimizationusingamodel of losses in induction motor drives”, Mathematics and Computers in Simulation,2006.

[2]. M.W. Turner, V.E. McCormick, J.G. Cleland,"Efficiency Optimization Control of AC Induction Motors", United States Environmental Protection Agency National Risk Management Research Laboratory,1996.

[3]. ABetka,A.Moussi,“Performanceoptimizationofaphotovoltaicinductionmotorpumpingsystem”,Renewable Energy, 2004.

[4]. SeydiVakkasUstun,MetinDemirtas,“Modelingandcontrol of V/f controlled induction motor using genetic-ANFIS algorithm”, Energy Conversion and Management, Vol. 50, Issue 3, 2009.

[5]. R.J.Spiegela,M.W.Turner,V.E.McCormick,“Fuzzy-logic-basedcontrollersforefficiencyoptimizationofinverter-fed induction motor drive”, Fuzzy Sets and Systems,2003.

[6]. FangLinLuo,HongYe,MuhammadRashid,“EnergyFactor Application in AC and DC Motor Drives”, Digital Power Electronics and Applications,2005.

[7]. Mehmet cunkas, Tahir Sag,“Efficiency determination of induction motors using multi-objective evolutionary algorithms”, Advances in Engineering Software, Vol. 41, Issue 2, 2010.

[8]. BhimSingh,BrijNandanSingh,R.B.Saxena,“Experience in the design optimization of a voltage source inverter fed squirrel cage induction motor”, Electric Power Systems Research, Vol. 26, Issue 2,1993.

[9]. S.Vaez-Zadeh,A.Payman,“Designandanalysisofsensorless torque optimization for single phase induction motors”, Energy Conversion and Management, 47,2006.

[10]. DavidCajander,HoangLeHuy,“Designandoptimizationofatorquecontrollerforaswitchedreluctancemotordrivefor electricvehiclesbysimulation”,MathematicsandComputers in Simulation 71,2006.

[11]. M. Hajian, G.R. Arab Markadeh, J. Soltani, S. Hoseinnia, “Energy optimized sliding-mode control of sensorless inductionmotordrives”,EnergyConversionandManagement 50 (2009).

[12]. D. C. Montgomery,“Design andAnalysis of Experiments”, John Wiley & Sons,2004.

[13]. N.Karayiannis,A.Venetanopulos,“ArtificialNeuralNetwork, Learning Algorithms, Performance and Applications”, Kluwer Academic Publishers,1993.

[14]. J.A.Bullinaria,“IntroductiontoNeuralNetworks”,University of Birmingham, 2003.

[15]. D. Goldberg,“Genetic Algorithm in Search, Optimization and Machine Learning”, Addison Wesley,1989.

[16]. C. Thanga Raj, S. P. Srivastava, Pramod Agarwal,"Energy Efficient Control of Three-Phase Induction Motor", InternationalJournalofComputerandElectricalEngineering, 2009.

[17]. StephenJ.Chapman,McGraw-Hill,"Electricmachineryand power system fundamentals,2002.

[18]. Electrical Transient Analyzer Program(ETAP),[Online]Available: http://www.etap.com

[19]. M. Damodar Reddy, Prof V.C. Veera Reddy,“Optimal Capacitor Placement using fuzzy and real coded genetic algorithmforMaximumsaving”,JournalofTheoreticaland Applied Information Technology”, pp. 219-224,2005.

[20]. R.L Haupt, S.L.Haupt,"Practical genetic algorithms", 2nd edition, John Wiley, 2004.

[21]. S. Russell, P. Norvig,"Artifical Intelligent: A Modern Approach", 2nd edition, Prentice Hall,2007