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**Linear Antenna Array Synthesis using the Enhanced
and Hybrid Cuckoo Search Metaheuristic Algorithms**

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Yours sincerely,

Khairul Najmy Haji Abdul Rani

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TABLE OF CONTENTS

CONTENTS	PAGE
DECLARATION OF THESIS	i
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	x
LIST OF ABBREVIATIONS	xvii
LIST OF SYMBOLS	xix
ABSTRAK	xxi
ABSTRACT	xxii
1 INTRODUCTION	1
1.1 Research Background	1
1.2 Research Motivation	3
1.3 Problem Statement	5
1.4 Research Objectives	8
1.5 Research Scope	9
1.6 Research Significance and Contribution	10
1.7 Thesis Organization	11
2 LITERATURE REVIEW	15
2.1 Introduction	15
2.2 Radiation Pattern Theory	19

2.3	Linear Antenna Array Theory	22
2.4	Justification of Synthesizing Antenna Array	23
2.5	Analytical Techniques in Smart Antenna Design	24
2.6	Numerical Methods in Smart Antenna Design	36
2.7	Evolutionary Computation or Evolutionary Algorithm Methods in Smart Antenna Design	42
2.8	Genetic Algorithm	45
2.9	Genetic Algorithm in Antenna Array Synthesis	47
2.10	Particle Swarm Optimization	51
2.11	Particle Swarm Optimization in Antenna Array Synthesis	55
2.12	Summary of Optimization Methods in Array Geometry Synthesis	60
2.13	Hybrid Optimization Algorithm	61
2.14	Multiobjective Optimization: Weighted-Sum and Pareto Front Optimum	61
3	RESEARCH METHODOLOGY	68
3.1	System Description	68
3.2	Cuckoo Search Algorithm	70
3.3	Cuckoo Search Algorithm in Linear Antenna Array Synthesis	76
4	SINGLE OBJECTIVE OPTIMIZATION	102
4.1	The Preliminary Study on Cuckoo Search Algorithm Internal Parameters	102

4.2	The Postulation of Modified Cuckoo Search Algorithm in Linear Antenna Array Synthesis	123
4.3	The Proposition of Modified Cuckoo Search Algorithm through Hybridization in Linear Antenna Array Synthesis	149
5	MULTIOBJECTIVE OPTIMIZATION	158
5.1	Multiobjective Optimization Techniques using Modified Cuckoo Search Algorithm in Linear Antenna Array Synthesis	158
5.1.1	Weighted–Sum Approach	158
5.1.2	Global Pareto Front Approach	171
6	RESULTS AND DISCUSSIONS	202
6.1	Cuckoo Search Algorithm Internal Parameters Analysis	202
6.2	Modified Cuckoo Search Algorithm Analysis	205
6.3	Hybrid Modified Cuckoo Search Algorithm Analysis	210
6.4	Multiobjective Optimization Approach of Modified Cuckoo Search Algorithm Analysis	213
6.4.1	Weighted–Sum Approach	213
6.4.2	Global Pareto Front Approach	215
6.5	Result Comparison	219
7	CONCLUSIONS AND RECOMMENDATIONS	221
7.1	Conclusions	221
7.2	Limitations	222
7.3	Future Work	224
	REFERENCES	226

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LIST OF TABLES

NO.	TITLE	PAGE
	Table 5.1: Optimization Methods for Antenna Array Synthesis	60
	Table 6.1: Design Parameter Specification.....	101
	Table 7.1: Optimal Location for α Comparison ($2N = 10$, Uniform, maxIter = 500)...	104
	Table 7.2: Optimal Location for α Comparison ($2N = 20$, Uniform, maxIter = 5000).	108
Table 7.3:	Optimal Location Distribution Type Comparison ($2N = 10$, Uniform, maxIter = 500)	110
Table 7.4:	Optimal Location Distribution Type Comparison ($2N = 20$, Uniform, maxIter = 10000)	112
Table 7.5:	Optimal Location for Step Factor Comparison ($2N = 10$, Uniform, maxIter = 500)	115
Table 7.6:	Optimal Location vs. Step Size Factor ($2N = 20$,Uniform, maxIter = 5000)	116
Table 7.7:	Optimal Location vs. Population ($2N = 10$, Uniform, maxIter = 500).....	119
Table 7.8:	Optimal Location for P_a Comparison ($2N = 10$,Uniform, maxIter = 500)..	121
Table 7.9:	Optimal Location for CS vs. MCS in α Value ($2N = 20$, Uniform, maxIter = 2000)	125
Table 7.10:	Optimal Location for CS vs. MCS in Distribution Type ($2N = 20$,Uniform, maxIter = 2000)	130
Table 7.11:	Optimal Location for CS vs. MCS in Nest ($2N = 20$, Uniform, maxIter = 2000)	133
Table 7.12:	Optimal Location for CS vs. MCS in P_a ($2N = 20$, Uniform, maxIter = 2000).....	136

Table 7.13: Optimal Location for CS vs. MCS in Distribution Type ($2N = 20$, Main Beam = 90° , Null = [45° , 135°], maxIter = 1000)	139
Table 7.14: Optimal Location for CS vs. MCS in Distribution Type ($2N = 20$, Dolph–Chebyshev, maxIter = 1000)	143
Table 7.15: Optimal Location for MCS vs. Other EC–Optimizers ($2N = 30$, Dolph–Chebyshev, maxIter = 1000)	148
Table 7.16: Optimal Location for MCS Hybrids vs. others ($2N = 20$, Uniform, maxIter = 1000)	151
Table 7.17: Optimal Location for MCS Hybrids vs. others ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°], maxIter = 100)	157
Table 8.1: Optimal Location for Weighted–Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000).....	163
Table 8.2: Optimal Amplitude for Weighted–Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000)	163
Table 8.3: Optimal Phase for Weighted–Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000)	164
Table 8.4: Optimal Location for Weighted–Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000)	170
Table 8.5: Optimal Amplitude for Weighted–Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000)	171
Table 8.6: Optimal Phase for Weighted–Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000)	171
Table 8.7: Selected Optimal Pareto Fitness for SPEA–based Arrays ($2N = 20$, Uniform, maxIter = 1000)	179

Table 8.8: Optimal Location for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	179
Table 8.9: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	180
Table 8.10: Optimal Phase for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	180
Table 8.11: Selected Optimal Pareto Fitness for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	183
Table 8.12: Optimal Location for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	190
Table 8.13: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	190
Table 8.14: Optimal Phase for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	190
Table 8.15: Selected Optimal Pareto Fitness for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000).....	199
Table 8.16: Optimal Location for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000).....	199
Table 8.17: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000).....	200
Table 8.18: Optimal Phase for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000).....	201
Table 9.1: EA/EC Stochastic Method Performance Comparison.....	220

LIST OF FIGURES

NO.	TITLE	PAGE
Figure 5.1:	(a) Switched-beam system coverage patterns, and (b) Adaptive array coverage (Stevanović, Skrivervik and Mosig, 2003).....	17
Figure 5.2:	Beamforming in an adaptive array system (Yilmazer et al., 2008).....	18
Figure 5.3:	Beamforming lobes and nulls that switched-beam (red), and Adaptive array (blue) systems with identical user signals (green line) and co-channel interferers (yellow lines) (Stevanović, Skrivervik and Mosig, 2003).....	18
Figure 5.4:	Radiation lobes of a three-dimensional (3D) antenna pattern.	20
Figure 5.5:	Linear plot of power pattern and its associated lobes and beamwidths.	20
Figure 5.6:	Amplitude taper (Keizer, 2009).....	26
Figure 5.7:	Normalized radiation pattern for amplitude-only synthesis (Keizer, 2009).	27
Figure 5.8:	Maximum peak SLL vs. Number of iterations (Keizer, 2009).	27
Figure 5.9:	Number of far-field directions violating the -45 dB SLL requirement, and number of far-field directions vs. Number of iterations (Keizer, 2009).....	28
Figure 5.10:	(i) Normalizing all other amplitudes by the edge element a_n (ii) The symmetry with amplitude a_0 at a distance of d from a_1 (Alexopoulos, 2006).	33
Figure 5.11:	AF as a function of u for $ SLL = 10$ dB with $N = 11$ (red) odd elements, and $N = 10$ (blue) even elements (Alexopoulos, 2006).	34
Figure 5.12:	Polar plot for AF as a function of u for $ SLL = 10$ dB with $N = 11$ (red) odd elements, and $N = 10$ (blue) even elements (Alexopoulos, 2006).....	34
Figure 5.13:	AF as a function of u for $ SLL = -13$ dB with $N = 17$ (red) odd elements, and $N = 20$ (blue) even elements (Alexopoulos, 2006).	35

Figure 5.14: Polar plot for AF as a function of u for $ SLL = -13$ dB with $N = 17$ (red) odd elements, and $N = 20$ (blue) even elements (Alexopoulos, 2006).	35
Figure 5.15: Array pattern for the Legendre functions synthesis (Gomez & Covarrubias, 2009).....	40
Figure 5.16: SLL when the main lobe steered in the range $-60^\circ \leq \theta_0 \leq 60^\circ$ for different space broadening factors, Δ (Gomez & Covarrubias, 2009).	41
Figure 5.17: HPBW when the main lobe steered in the range $-60^\circ \leq \theta_0 \leq 60^\circ$ for different space broadening factors, Δ (Gomez & Covarrubias, 2009).	41
Figure 5.18: Best array pattern found by RGA for the 12-element array case with an improved null; i.e., $h = 60^\circ$ and $h = 120^\circ$ (Goswami and Mandal, 2012).	51
Figure 5.19: Convergence rate plot for the 10-element array case (Goudos et al., 2010).	58
Figure 5.20: Array pattern for the 10-element array case with SLL suppression and desired beamwidth at 23° (Goudos et al., 2010).....	59
Figure 5.21: Left: Pareto optimality in objective space, and Right: Possible relations of solutions in objective space (Zitzler, 1999).	63
Figure 5.22: Non-convex part of the Pareto front (Ryu, Kim & Wan, 2009).....	66
Figure 6.1: Block Diagram of Research Methodology.....	68
Figure 6.2: Geometry of the $2N$ -element symmetric linear array.....	69
Figure 6.3: Flowchart of the Original CS Algorithm.....	73
Figure 6.4: Flowchart of the Proposed MCS Algorithm	79
Figure 6.5: Flowchart of the Proposed MCSPSO Algorithm	83
Figure 6.6: Flowchart of the Proposed MCSGA Algorithm.....	84
Figure 6.7: Flowchart of the Proposed MCSSPEA Algorithm.....	91
Figure 6.8: Flowchart of the Proposed MCSPSOSPEA Algorithm	92

Figure 6.9: Flowchart of the Proposed MCSHCSPEA Algorithm	98
Figure 7.1: Normalized Pattern for α Comparison ($2N = 10$, Uniform, maxIter = 500)	103
Figure 7.2: Polar Pattern for CS-based Array ($2N=10$, Gaussian, Uniform, maxIter = 500).....	104
Figure 7.3: Polar Pattern for CS-based Array ($2N=10$, Cauchy, Uniform, maxIter = 500)	105
Figure 7.4: Location and Fitness Curves for α Comparison ($2N=10$, Uniform, maxIter = 500)	105
Figure 7.5: Normalized Pattern for α Comparison ($2N = 20$, Uniform, maxIter = 5000)	107
Figure 7.6: Location and Fitness Curves for α Comparison ($2N = 20$, Uniform, maxIter = 5000).....	108
Figure 7.7: Normalized Pattern for Distribution Type Comparison ($2N = 10$, Uniform, maxIter = 500)	109
Figure 7.8: Location and Fitness Curves for Distribution Type Comparison ($2N = 10$, Uniform, maxIter = 500)	110
Figure 7.9: Normalized Pattern for Distribution Type Comparison ($2N = 20$, Uniform, maxIter = 10000)	111
Figure 7.10: Location and Fitness Curves for Distribution Type Comparison ($2N = 20$, Uniform, maxIter = 10000)	112
Figure 7.11: Normalized Pattern Step Factor Comparison ($2N = 10$, Uniform, maxIter = 500)	114
Figure 7.12: Location and Fitness Curves for Step Factor Comparison ($2N = 10$, Uniform, maxIter = 500)	114

Figure 7.13: Normalized Pattern for Step Factor Comparison ($2N = 20$, Uniform, maxIter = 5000)	115
Figure 7.14: Location and Fitness Curves for Step Factor Comparison ($2N = 20$, Uniform, maxIter = 5000)	116
Figure 7.15: Normalized Pattern vs. Population ($2N = 10$, Uniform, maxIter = 500)..	118
Figure 7.16: Location and Fitness Curves ($2N = 10$, Uniform, maxIter = 500)	118
Figure 7.17: Normalized Pattern for P_a Comparison ($2N = 10$, Uniform, maxIter = 500)	120
Figure 7.18: Location and Fitness Curves for P_a Comparison ($2N = 10$, Uniform, maxIter = 500)	121
Figure 7.19: Normalized Pattern for CS vs. MCS in α Value ($2N = 20$, Uniform, maxIter = 2000)	124
Figure 7.20: Location and Fitness Curves for CS vs. MCS in α Value ($2N = 20$, Uniform, maxIter = 2000)	124
Figure 7.21: Normalized Pattern for CS vs. MCS in Distribution Type ($2N = 20$, Uniform, maxIter = 2000)	127
Figure 7.22: Location and Fitness Curves for CS vs. MCS in Distribution Type ($2N = 20$, Uniform, maxIter = 2000)	129
Figure 7.23: Normalized Pattern for CS vs. MCS in Nest ($2N = 20$, Uniform, maxIter = 2000)	132
Figure 7.24: Location and Fitness Curves for CS vs. MCS in Nest ($2N = 20$, Uniform, maxIter = 2000)	132
Figure 7.25: Normalized Pattern for CS vs. MCS in P_a ($2N = 20$, Uniform, maxIter = 2000)	135

Figure 7.26: Location and Fitness Curves for CS vs. MCS in P_a ($2N = 20$, Uniform, maxIter = 2000)	135
Figure 7.27: Normalized Pattern for CS vs. MCS in Distribution Type ($2N = 20$, Main Beam = 90° , Null = [45° , 135°], maxIter = 1000)	138
Figure 7.28: Location and Fitness Curves for CS vs. MCS in Distribution Type ($2N = 20$, Main Beam = 90° , Null = [45° , 135°]).....	139
Figure 7.29: The Dolph–Chebyshev Excitation Amplitude for $2N = 20$ Linear Array	141
Figure 7.30: Normalized Pattern for CS vs. MCS in Distribution Type ($2N = 20$, Dolph–Chebyshev, maxIter = 1000)	142
Figure 7.31: Location and Fitness Curves for CS vs. MCS in Distribution Type ($2N = 20$, Dolph–Chebyshev, maxIter = 1000).....	143
Figure 7.32: The Dolph–Chebyshev Excitation Amplitude for $2N = 30$ Linear Array	145
Figure 7.33: Normalized Pattern for MCS vs. Other EC–Optimizers ($2N = 30$, Dolph–Chebyshev, maxIter = 1000)	146
Figure 7.34: Location and Fitness Curves for MCS vs. Other EC–Optimizers ($2N = 30$, Dolph–Chebyshev, maxIter = 1000)	147
Figure 7.35: Normalized Pattern for MCS Hybrids vs. others ($2N = 20$, Uniform, maxIter = 1000)	150
Figure 7.36: Location and Fitness Curves for MCS Hybrids vs. others ($2N = 20$, Uniform, maxIter = 1000)	151
Figure 7.37: Normalized Pattern for MCS Hybrids vs. others ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°], maxIter = 100).....	154
Figure 7.38: Polar Pattern for Conventional Array ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°]).....	155

Figure 7.39: Polar Pattern for MCSPSO Array ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°]).....	155
Figure 7.40: Polar Pattern for MCSGA Array ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°]).....	156
Figure 7.41: Location and Fitness Curves for MCS Hybrids vs. others ($2N = 10$, Main Beam = 60° , Null = [30° , 31° , 79° , 80°]).....	156
Figure 8.1: Normalized Pattern for Weighted-Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000)	160
Figure 8.2: Optimal Location and Total Fitness Curves for Weighted-Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000).....	161
Figure 8.3: Optimal Amplitude for Weighted-Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000)	162
Figure 8.4: Optimal Phase for Weighted-Sum MCS Hybrids vs. others ($2N = 10$, Uniform, maxIter = 1000)	162
Figure 8.5: Normalized Pattern for Weighted-Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000).....	167
Figure 8.6: Optimal Location and Total Fitness Curves for Weighted-Sum MCS Hybrids vs. others	168
Figure 8.7: Optimal Amplitude for Weighted-Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000).....	169
Figure 8.8: Optimal Phase for Weighted-Sum MCS Hybrids vs. others ($2N = 20$, Uniform, Null = [35° , 145°], maxIter = 1000).....	169
Figure 8.9: Strength Pareto Evolutionary Algorithm (SPEA) Front Approximations ($2N = 20$, Uniform, maxIter = 1000)	175

Figure 8.10: Normalized Pattern for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	177
Figure 8.11: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	178
Figure 8.12: Optimal Phase for SPEA-based Arrays ($2N = 20$, Uniform, maxIter = 1000)	178
Figure 8.13: Strength Pareto Evolutionary Algorithm (SPEA) Front Approximations ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	185
Figure 8.14: Normalized Pattern for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	187
Figure 8.15: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	188
Figure 8.16: Optimal Phase for SPEA-based Arrays ($2N = 20$, Dolph-Chebyshev, maxIter = 1000)	188
Figure 8.17: Strength Pareto Evolutionary Algorithm (SPEA) Front Approximations ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000)	194
Figure 8.18: Normalized Pattern for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000)	197
Figure 8.19: Optimal Amplitude for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000)	197
Figure 8.20: Optimal Phase for SPEA-based Arrays ($2N = 20$, Uniform, Null = $[30^\circ, 31^\circ, 149^\circ, 150^\circ]$, maxIter = 1000)	198

LIST OF ABBREVIATIONS

ACO	ant colony optimization
AF	array factor
AGA	adaptive-parameter genetic algorithm
BBCA	big bang crunch algorithm
BGA	binary-coded genetic algorithm
CGM	conjugate gradient method
CLPSO	comprehensive learning particle swarm optimization
CS	cuckoo search
DE	differential evolution
DSP	digital signal processing
EA	evolutionary algorithm
EC	evolutionary computation
FA	firefly algorithm
FNBW	first-null beamwidth
GA	genetic algorithm
HC	hill climbing
HPBW	half-power beamwidth
IEEE	Institute of Electrical and Electronics Engineers
IFT	iterative Fourier technique
IWO	invasive weed optimization
MA	memetic algorithm
MCS	modified cuckoo search
MO	multiobjective
PS	pattern search

PSO	particle swarm optimization
CLPSO	comprehensive learning particle swarm optimization
QoS	quality of service
RGA	real-coded genetic algorithm
SA	simulated annealing
SADE	self-adaptive differential evolution
SO	single objective
SLL	side lobe level
SPEA	strength Pareto evolutionary algorithm
TM	Taguchi's method
TS	tabu search

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LIST OF SYMBOLS

w	CS algorithm inertia weight
P_a	CS algorithm fraction probability or discovery rate
p_{best}	PSO algorithm individual personal best
g_{best}	PSO algorithm population global best
f_{min}	minimum fitness
A_n or I_n	current excitation amplitude of the n th element
k	free space wavenumber
λ	wavelength
d	spacing between two consecutive elements
α_n or φ_n or ϕ_n	current excitation phase of the n th element
θ or θ_d or θ_0	zenith angle measured from the line of the array or direction of main lobe
R	maximum side lobe level ratio
$P_n(x)$	Legendre polynomials compact expression
$F(\alpha_p)$	Legendre transformation application to the array factor
$f(\alpha, \beta)$	Legendre polynomial of fractional order
p_c	GA crossover rate for chromosome
p_m	GA mutation rate for chromosome
v_{id}	PSO velocity of the i th particle and d th dimension
p_{id}	PSO personal best of the i th particle and d th dimension
p_{gd}	PSO global best of the population and d th dimension
x_{id}	PSO position of the i th particle and d th dimension
P_c	CLPSO learning probability
BW_c	calculated beamwidth
BW_d	desired beamwidth

C_{dB}	desired null level in dB
θ_k	direction of the k th null
x_i^{t+1}	new CS solution for the i th cuckoo and the $t + 1$ iteration
$I_H(A)$	Pareto fronts hypervolume indicator
$vol(.)$	Lebesgue measure

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Sintesis Jalur Antena Linear menerusi Pemantapan dan Hibrid Algoritma Metaheuristik Pencarian Burung Sewah

ABSTRAK

Sintesis geometri berperanan penting menentukan susunatur fizikal sesuatu susunan antena untuk penjanaan polar radiasi menyerupai polar radiasi sebenar yang diperlukan. Sintesis dapat direalisasikan dengan mengenalpasti lokasi elemen-elemen susunan antena serta menentukan amplitud dan fasa pengujaan arus sesuai digunakan pada elemen-elemen susunan antena. Pelbagai teknik sintesis dilakukan untuk mengecilkan tahap sisi cuping (SLL) dan/atau mengurangkan nol sambil mengekalkan atau meningkatkan intensiti radiasi cuping utama. Banyak kajian menunjukkan pelbagai teknik konvensional analitikal, numerikal, dan algoritma evolusi (EA) atau pengiraan evolusi (EC) moden mempunyai kelemahan tertentu di dalam sintesis geometri susunan antena. Ini termasuk, pengembangan lebar rasuk dan ketepatan pengarah di dalam runcingan amplitud, kelemahan pencarian menyeluruh di dalam kaedah analitikal, kurang keseimbangan di antara pemecut-pemecut pencarian lokal dan global di dalam pengoptimuman sekumpulan partikel (PSO), dan kelemahan pengeoperasi-pengeoperasi pindah silang dan mutasi di dalam algoritma genetik (GA). Tesis ini membentangkan pembangunan berperingkat algoritma metaheuristik dimantap dan hibrid pencarian burung sewah (CS) sebagai alternatif teknik EA/EC untuk sintesis susunan antena linear bersimetri. Pertamanya, cadangan algoritma diubahsuai CS (MCS) melalui integrasi dengan pengoperasi pemilihan roda Roulette, pemberat inersia dinamik dan kadar penemuan penyelesaian dinamik bagi mengawal eksplorasi penyelesaian terbaik untuk pengoptimuman fungsi satu objektif (SO). Keduanya, memperkenalkan algoritma hibrid MCS dengan PSO (MCSPSO) dan hibrid MCS dengan GA (MCSGA) digunakan di dalam kaedah-kaedah pengoptimuman fungsi SO dan fungsi pelbagai objektif (MO) berasaskan campuran pemberat. Ketiganya, dicadangkan juga hibrid algoritma MCS dengan algoritma evolusi kekuatan Pareto (MCSSPEA), hibrid pencarian dakian bukit (HC) dengan algoritma MCSSPEA (MCSHCSPEA), dan hibrid PSO dengan algoritma MCSSPEA (MCSPSOSPEA) dilengkapi dengan rumusan pengembangan jarak untuk mengurangkan masalah perangkap lokal. Ini adalah teknik-teknik terbaru khas pengoptimuman Pareto fungsi MO untuk mencari penyelesaian yang dominan meliputi lokasi, pengujaan amplitud dan pengujaan fasa arus. Kesemua pembangunan algoritma yang diuji, penulisan kod sumber dan penjanaan keputusan dibuat menggunakan perisian saintifik MATLAB. Penyelesaian-penyelesaian optimum simulasi kemudiannya dibandingkan dengan penyelesaian-penyelesaian lain yang setara. Berdasarkan keputusan simulasi, algoritma cadangan MCSPSO mengatasi lain-lain algoritma SO dan MO berasaskan campuran pemberat, manakala algoritma cadangan MCSPSOSPEA mengatasi lain-lain algoritma MO berasaskan Pareto yang diuji untuk pengecilan SLL dan/atau pengurangan nol di samping mencapai kearah antena linear yang tinggi dan lebar berkas sinar (HPBW) yang kecil pada cuping utama.

Linear Antenna Array Synthesis using the Enhanced and Hybrid Cuckoo Search Metaheuristic Algorithm

ABSTRACT

The antenna geometry synthesis plays an important role to determine the physical layout of the antenna array, which produces the radiation pattern closest to the actual desired pattern. The synthesis can be realized by defining the location of antenna array elements, and by choosing suitable excitation of amplitude, and excitation phase applied on the antenna array elements. Many synthesis techniques are done through suppressing the side lobe level (SLL) and/or mitigating prescribed nulls while simultaneously maintaining or improving the major lobe radiation intensity. Studies show that some conventional analytical, numerical, and modern evolutionary algorithm (EA) or evolutionary computation (EC) techniques have certain limitations in antenna array geometry synthesis. This includes beamwidth expanding and directivity saturation in amplitude tapering, exhaustive checking impairment in analytical method, disparity predicament between local and global search accelerators in particle swarm optimization (PSO), and drawbacks of crossover and mutation operators in genetic algorithm (GA). This thesis presents the sequential development of enhanced and hybrid versions of cuckoo search (CS) metaheuristic algorithm as an alternative of EA/EC technique for symmetric linear antenna array synthesis. Firstly, the proposal of the modified CS (MCS) algorithm through the integration with the Roulette wheel selection operator, dynamic inertia weight, and dynamic discovery rate controlling the best solutions exploration for a single objective (SO) optimization. Secondly, there is the hybridization of MCS with PSO (MCSPSO), and MCS with GA (MCSSGA) in both SO and weighted-sum multiobjective (MO) approaches. Thirdly, the proposed amalgamation of MCS with strength Pareto evolutionary algorithm (MCSSPEA), hill climbing (HC) stochastic method within MCSSPEA algorithm (MCSHCSSPEA), and PSO within MCSSPEA algorithm (MCSPSOSPEA) equipped with distance expansion formulae to reduce local trap problem. These newly techniques are specifically for Pareto MO optimization to find non-dominated solutions including element location, excitation amplitude, and excitation phase. All the tested algorithms development, source code writing, and results execution are performed using MATLAB scientific software. The optimal solutions are then compared against corresponding counterparts. Based on simulation results, the proposed MCSPSO outperforms other SO and weighted-sum MO algorithms whereas the proposed MCSPSOSPEA algorithm surpasses other tested Pareto MO algorithms in SLL suppression and/or nulls mitigation whilst achieving a high linear antenna directivity, and small half-power beamwidth (HPBW), respectively.

CHAPTER ONE

INTRODUCTION

1.1 Research Background

Many studies have been done extensively for developing methods to improve wireless systems performance. These includes “smart antenna” or “intelligent antenna” design, which becomes as one of the leading technologies to achieve high efficiency networks, maximize capacity and improve quality of service (QoS) and increase coverage (Balanis & Ioannides, 2007). Generally, there are two categories of smart antennas, which are “switched-beam antennas” and “adaptive antenna arrays” (Mouhamadou & Vaudon, 2006 and Jain, Katiyar & Agrawal, 2011).

The switched-beam antenna forms several fixed beam patterns, which could heighten sensitivity in particular directions. The switched-beam antenna detects signal strength, choose from one of several predetermined, fixed beams, and switch from one beam to another as the receiver moves throughout the sector. Although this approach does not provide complete flexibility, it simplifies the smart antenna design and provides sufficient level of adaptation for many applications.

On the other hand, the adaptive antennas signify the most advanced smart antenna approach to date. Adaptive antenna differs from the conventional antenna in the sense capable of adjusting antenna array weights automatically to generate an optimal radiation pattern for user (Banerjee & Dwivedi, 2013). Through a variety of new digital signal processing (DSP) algorithms, the adaptive antenna exploits its capability to locate and track various types of signals effectively. In this case, the

adaptive antenna arrays can dynamically maximize intended signal reception (main lobe) and/or minimize interference or null simultaneously.

Precisely, Banerjee & Dwivedi (2013) stated that adaptive antenna arrays allow the beam to be continually steered to any direction to allow for the maximum signal to be received and/or minimum of nulls. In this case, we can use adaptive beamforming techniques to obtain the desired antenna radiation pattern by adjusting the antenna parameters such as position, excitation current amplitude and excitation current phase weights of the antenna array elements. Radiation pattern nulling optimization techniques are very important to suppress undesired interfering signals while preserving the desired main beam intensity.

Overall, both switched-beam and adaptive antennas are able to provide the directivity. Yet, for antenna designers and engineers, decisions need to be made against cost, complexity and the optimal performance requirements to decide which type should be used to cater the vastly demanding bandwidth, QoS and coverage of wireless communication systems.

Smart antennas design has attracted a widespread interest for several decades due to their implementations in numerous applications (Godara, 2004) and their capabilities to increase system performance. This becomes beneficial in urban and densely populated area where smart antennas can dynamically tuning out interference while focusing on the intended user signal via remarkable DSP advanced techniques (Balanis & Ioannides, 2007). The first issue of *IEEE Transactions of Antennas and Propagation* published in 1964, was followed by special issues of various journals, books, a selected bibliography, and a vast number of specialized research papers (Godara, 2004). Some of the selected papers examples related to smart antenna design include adaptive antenna systems (Widrow et al., 1967), adaptive arrays (Applebaum,