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

By

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A thesis submitted in fulfilment of the requirements for the degree of
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UNIVERSITI MALAYSIA PERLIS**

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Yours sincerely,

Khairul Najmy Haji Abdul Rani

Ph.D. candidate

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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