

A HYBRID KIDNEY ALGORITHM
STRATEGY FOR COMBINATORIAL
INTERACTION TESTING PROBLEM

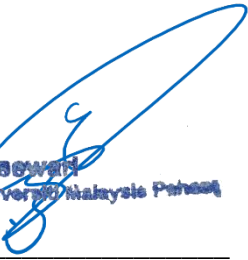
AMEEN ALI MOHAMMED BA HOMAID

DOCTOR OF PHILOSOPHY

UNIVERSITI MALAYSIA PAHANG

SUPERVISOR'S DECLARATION

We hereby declare that We have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award the degree of the Doctor of Philosophy.



**Assoc. Prof. Ts. Dr.
AbdulRahman A. Alsewari**
Faculty of Computing, Universiti Malaysia Pahang
+66174254911
alsewari@ump.edu.my
alsewari@ieee.org

(Supervisor's Signature)

Full Name : TS. DR. ABDULRAHMAN AHMED MOHAMMED AL-SEWARI

Position : ASSOCIATE PROFESSOR

Date : 11/2/2022



PROFESSOR DR. KAMAL ZUHARI BIN ZAMLI
Deputy vice Chancellor
(Research & Innovation)
Universiti Malaysia Pahang
26600 Pekan
Pahang Darul Makmur

(Co-supervisor's Signature)

Full Name : TS. DR. KAMAL ZUHARI BIN ZAMLI

Position : PROFESSOR

Date : 11/2/2022



STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

A handwritten signature in blue ink, appearing to be 'AMEEN ALI MOHAMMED BA HOMAID', is written above a horizontal line.

(Student's Signature)

Full Name : AMEEN ALI MOHAMMED BA HOMAID

ID Number : PCS16003

Date : February 2022

A HYBRID KIDNEY ALGORITHM STRATEGY
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ABSTRAK

Pengujian Interaksi Kombinatorik (CIT) menjana sampel set kes ujian (Sut Ujian Akhir (FTS)) dan bukannya kesemua kemungkinan kes ujian. Penjanaan FTS dengan saiz optimum adalah masalah pengoptimuman komputasi dan juga masalah Polinomial Tidak Deterministik Keras (NP-hard). Kajian terbaharu telah mengimplementasi algoritma metaheuristik sebagai asas strategi CIT. Walaupun strategi hibrid CIT menjana saiz SUT yang kompetitif, tiada strategi tunggal yang berjaya mengatasi antara satu sama lain dengan jayanya pada keseluruhan kes. Tambahan pula, strategi hibrid memerlukan lebih masa larian daripada strategi algoritma asal. Algoritma Ginjal (KA) adalah satu algoritma metaheuristik terkini yang mempunyai kecekapan dan prestasi tinggi dalam menyelesaikan masalah pengoptimuman yang berbeza serta mengatasi kebanyakan algoritma metaheuristik sedia ada, Namun, KA mempunyai kelemahan dalam proses eksploitasi dan eksplorasi dengan keperluan pengimbangan yang perlu dipertingkatkan. Kekurangan ini menyebabkan KA mudah terjerumus kepada optimum tempatan. Kajian ini mencadangkan penghibridan KA tahap rendah dengan pengendali mutasi serta menambahbaik proses penyaringan KA untuk membentuk Algoritma Ginjal (HKA) yang baharu. HKA menangani kelemahan dalam KA dengan meningkatkan proses eksplorasi dan eksploitasi algoritma melalui hibridisasi dengan operator mutasi, dan menambahbaik proses pengimbangan dengan meningkatkan proses penyaringannya. HKA berjaya meningkatkan kecekapan dari segi penghasilan ukuran FTS yang optimum dan meningkatkan prestasi dari segi masa penjanaan. HKA telah diadaptasi dalam strategi CIT sebagai Strategi CIT berasaskan HKA (HKAS) untuk menghasilkan ukuran FTS yang paling optimum. Hasil HKAS menunjukkan bahawa HKAS dapat menghasilkan ukuran FTS optimum di lebih daripada 67% eksperimen penanda aras serta menyumbang sebanyak 34 ukuran FTS optimum baru. HKAS juga mempunyai kecekapan dan prestasi yang lebih baik daripada KAS. HKAS adalah strategi CIT berasaskan metaheuristik hibrid pertama yang menghasilkan ukuran FTS optimum dengan masa penjanaan yang lebih baik daripada strategi CIT berasaskan algoritma asal. Selain daripada menyokong ciri CIT yang berbeza: seragam / VS CIT, IOR CIT serta kekuatan interaksi hingga 6, kajian ini memperkenalkan juga satu lagi varian KA iaitu KA Penambahbaikan (IKA) dan KA Mutasi (MKA) serta tambahan strategi baru CIT yang berasaskan IKA (IKAS) dan MKA (MKAS).

ABSTRACT

Combinatorial Interaction Testing (CIT) generates a sampled test case set (Final Test Suite (FTS)) instead of all possible test cases. Generating the FTS with the optimum size is a computational optimization problem (COP) as well as a Non-deterministic Polynomial hard (NP-hard) problem. Recent studies have implemented hybrid metaheuristic algorithms as the basis for CIT strategy. However, the existing hybrid metaheuristic-based CIT strategies generate a competitive FTS size, there is no single CIT strategy can overcome others existing in all cases. In addition, the hybrid metaheuristic-based CIT strategies require more execution time than their own original algorithm-based strategies. Kidney Algorithm (KA) is a recent metaheuristic algorithm and has high efficiency and performance in solving different optimization problems against most of the state-of-the-art of metaheuristic algorithms. However, KA has limitations in the exploitation and exploration processes as well as the balancing control process is needed to be improved. These shortages cause KA to fail easily into the local optimum. This study proposes a low-level hybridization of KA with the mutation operator and improve the filtration process in KA to form a recently Hybrid Kidney Algorithm (HKA). HKA addresses the limitations in KA by improving the algorithm's exploration and exploitation processes by hybridizing KA with mutation operator, and improve the balancing control process by enhancing the filtration process in KA. HKA improves the efficiency in terms of generating an optimum FTS size and enhances the performance in terms of the execution time. HKA has been adopted into the CIT strategy as HKA based CIT Strategy (HKAS) to generate the most optimum FTS size. The results of HKAS shows that HKAS can generate the optimum FTS size in more than 67% of the benchmarking experiments as well as contributes by 34 new optimum size of FTS. HKAS also has better efficiency and performance than KAS. HKAS is the first hybrid metaheuristic-based CIT strategy that generates an optimum FTS size with less execution time than the original algorithm-based CIT strategy. Apart from supporting different CIT features: uniform/Vs CIT, IOR CIT as well as the interaction strength up to 6, this study also introduces another recently variant of KA which are Improved KA (IKA) and Mutation KA (MKA) as well as new CIT strategies which are IKA-based (IKAS) and MKA-based (MKAS).

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