SIMULATED KALMAN FILTER ALGORITHMS FOR SOLVING OPTIMIZATION PROBLEMS

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Doctor of Philosophy

UNIVERSITI MALAYSIA PAHANG

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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.

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ABSTRAK

Pengoptimuman merupakan proses penting dalam menyelesaikan masalah kejuruteraan. Malangnya, banyak masalah pengoptimuman praktikal tidak dapat diselesaikan dengan optimal dalam usaha pengiraan yang munasabah. Pengoptimuman jalur gerudi misalnya, boleh membawa kepada pengurangan masa proses pengilangan yang ketara, lantas dapat mengurangkan kos pengeluaran yang besar. Pengurangan jumlah masa perjalanan mesin penggerudian khususnya adalah isu yang paling penting dalam pengeluaran jumlah besar papan litar bercetak (PCB) di industri perkilangan elektronik. Apabila penyelesaian yang tepat bukanlah pilihan atau mungkin tidak perlu, seseorang boleh menggunakan pendekatan metaheuristik untuk mendapatkan penyelesaian yang hampir optimal dalam beberapa masa pengiraan yang munasabah. Dalam kajian ini, dua algoritma pengoptimuman metaheuristik baru yang dinamakan sebagai simulasi penuras Kalman (SKF), dan solusi tunggal simulasi penuras Kalman (ssSKF) diperkenalkan untuk masalah pengoptimuman global. Kedua-dua algoritma ini diilhamkan oleh keupayaan anggaran kaedah pengiraan penuras Kalman yang terkenal. Penuras Kalman yang dinamakan sempena penciptanya, merupakan algoritma yang luar biasa kerana ia dapat dibuktikan sebagai kaedah pengiraan optimum Gaussian sejajar. Ini telah memberi inspirasi kepada penciptaan algoritma metaheuristik yang dipanggil algoritma heuristik Kalman (HKA) pada tahun 2009. Aplikasi dan pengembangan algoritma HKA menunjukkan bahawa algoritma pengoptimuman berdasarkan prinsip anggaran mempunyai potensi besar dalam menyelesaikan pelbagai masalah pengoptimuman. Walaubagaimanapun, algoritma HKA mempunyai kelemahannya tersendiri. Walaupun ia diperkenalkan sebagai algoritma pengoptimuman stokastik berasaskan populasi, HKA bukanlah algoritma berasaskan populasi kerana ia memulakan dan mengemaskini solusi tunggal. Pengiraan dalam HKA juga menjadi mahal apabila berurusan dengan dimensi tinggi. Akhir sekali, HKA mempunyai kebergantungan yang sangat tinggi terhadap andaian Gaussian. Algoritma SKF dan ssSKF menggunakan model skalar penuras Kalman yang berasingan sebagai strategi pencarian untuk mengatasi kekurangan ini. Pada dasarnya, masalah pengoptimuman dianggap sebagai proses anggaran. Setiap ejen bertindak sebagai penuras Kalman dan mencari penyelesaian kepada masalah pengoptimuman dengan menggunakan kerangka penuras Kalman yang standard, yang merangkumi fasa ramalan, fasa pengukuran simulasi dan fasa anggaran dengan penyelesaian yang paling baik sebagai rujukan. Algoritma-algoritma tersebut dinilai menggunakan 30 fungsi penanda aras CEC2014, dan kemudiannya digunakan untuk menyelesaikan kajian pembelajaran jalur gerudi papan litar bercetak. Analisis statistik Wilcoxon menunjukkan algoritma ssSKF yang menggunakan persekitaran tempatan secara adaptif dalam fasa ramalan memberi penyelesaian yang lebih baik daripada algoritma SKF berasakan populasi yang menggunakan anggaran terakhir sebagai ramalannya, terutamanya dalam penyelesaikan fungsi dimensi tinggi. Proses menanda aras dengan algoritma-algoritma baru yang diuji dengan set penanda aras CEC2014 menunjukkan semua algoritma yang dibandingkan mempunyai purata penyelesaikan setara. Analisis Friedman meletakkan algoritma ssSKF pada tahap ketiga manakala algoritma SKF berasaskan populasi pada tahap keempat apabila ditanda-aras terhadap tiga algoritma canggih yang bertanding dalam pertandingan CEC2014. Dalam menanda aras prestasi algoritma SKF dan ssSKF dalam menyelesaikan kajian pembelajaran 14-lubang PCB, secara purata, kedua-dua algoritma berupaya menyelesaikannya secara optimum pada bilangan penilaian fungsi yang lebih sedikit berbanding algoritma lain, walaupun tidak mencukupi untuk menandingi algoritma Taguchi-Genetic Algorithm.

ABSTRACT

Optimization is an important process in solving most engineering problems. Unfortunately, many practical optimization problems cannot be solved to optimality within reasonable computational effort. Optimization in drill path for example, can lead to a significant time reduction in the overall manufacturing process, thus reducing a significant amount of total production costs. Reduction of the total travelling time of the drilling machine in particular, is the most crucial issue in large production of electronics manufacturing industries involving printed circuit board (PCB). When the exact solution is not an option or probably unnecessary, one may use metaheuristic approach to obtain a near-optimal solution in some reasonable computational time. In this research, two novel estimation-based metaheuristic optimization algorithms, named as Simulated Kalman Filter (SKF), and single-solution Simulated Kalman Filter (ssSKF) algorithms are introduced for global optimization problems. These algorithms are inspired by the estimation capability of the well-known Kalman filter estimation method. Kalman filter, named after its developer, is a very rare algorithm that is provable to be an optimal linear Gaussian estimator. Its optimality has inspired the development of a metaheuristic algorithm called Heuristic Kalman Algorithm (HKA) in 2009. Applications and improvements to the HKA algorithm suggest that optimization algorithm based on estimation principle has a huge potential in solving a wide variety of optimization problems. However, the HKA algorithm has its own flaws. Although it was introduced as a population-based stochastic optimization algorithm, HKA is not exactly a population-based algorithm because it initializes and updates only a single solution. The computation in HKA also becomes expensive when dealing with high dimension. Last but not least, HKA has a very high dependency on the Gaussian assumption. The proposed population-based SKF algorithm and the single solution-based SKF algorithm use the scalar model of discrete Kalman filter algorithm as the search strategy to overcome these flaws. In principle, the optimization problem is regarded as a state estimation process. Each agent acts as a Kalman filter and finds solution to the optimization problem using a standard Kalman Filter framework which comprises of prediction, simulated measurement, and estimation phase that uses the best-so-far solution as a reference. The algorithms are evaluated using 30 benchmark functions of the CEC2014 benchmark suite, and then applied to solve PCB drill path optimization case study. The Wilcoxon signed ranked statistical test shows that the ssSKF algorithm that uses an adaptive local neighbourhood in the prediction phase performs statistically better than the SKF algorithm that uses the last estimated state as its prediction, especially in solving high dimensional functions. Benchmarking with recent algorithms tested on the CEC2014 benchmark suite shows that all compared algorithms perform statistically on par considering their average performance. The Friedman test ranked ssSKF and SKF algorithm in the third and fourth rank respectively when they are being benchmarked against three state-of-the-art algorithms that competed in the CEC2014 competition. In the benchmarking of the SKF and ssSKF algorithms' performance in solving the 14-hole PCB drill path optimization case study with recent implementations, on average, both algorithms show the ability to converge to the optimal solution at a smaller number of function evaluations compared to the Gravitational Search Algorithm (GSA), Cuckoo Search (CS), and Intelligent Water Drop (IWD), although fall-short to the Taguchi-Genetic Algorithm optimization algorithm.

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α	Adaptive coefficient
δ_t	Step size
δ_0	Initial step size
N_s	Local neighbourhood

LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
CEC	Congress on Evolutionary Computation
CS	Cuckoo Search
COA	Cognitive behaviour Optimization Algorithm
DE	Differential Evolution
EA/EC	Evolutionary Algorithm/Evolutionary Computation
GA	Genetic Algorithm
GSA	Gravitational Search Algorithm
HKA	Heuristic Kalman Algorithm
IWD	Intelligent Water Drop
L-SHADE	Success History-based Adaptation Differential Evolution with Linear population size reduction
MATLAB	Matrix Laboratory
MT	Multi Tool
NFL	No Free Lunch
NRGA	Non-uniform mapping in Real-coded Real-coded Genetic Algorithm
OptBees	Bee-inspired algorithm for Optimization
SKF	Simulated Kalman Filter
SI	Swarm Intelligence
ssSKF	Single-solution Simulated Kalman Filter
ST	Single Tool
PBA	Pity Beetle Algorithm
PCB	Printed Circuit Board
PSO	Particle Swarm Optimization
TSP	Travelling Salesman Problem

REFERENCES

Abbas, A. T., Hamza, K., & Aly, M. F. (2014). CNC Machining Path Planning Optimization for Circular Hole Patterns via a Hybrid Ant Colony Optimization Approach. *Mechanical Engineering Research*, *4*(2), 16–29.

Abdullah, E. A., Ahmed Saleh, I., & Al Saif, O. I. (2018). Performance Evaluation of Parallel Particle Swarm Optimization for Multicore Environment. In *ICOASE 2018 - International Conference on Advanced Science and Engineering* (pp. 81–86). IEEE.

Abdullah, H., Ramli, R., Wahab, D. A., & Qudeiri, J. A. (2015). Simulation Approach of Cutting Tool, (June), 35–44.

Abed-alguni, B. H., & Barhoush, M. (2018). Distributed Grey Wolf Optimizer for Numerical Optimization Problems. *Jordanian Journal of Computers and Information Technology*, *4*(3), 130–149.

Adam, A., Zainal Abidin, A. F., Ibrahim, Z., Husain, A. R., Md Yusof, Z., & Ibrahim, I. (2010). A particle swarm optimization approach to Robotic Drill route optimization. In *AMS2010: Asia Modelling Symposium 2010 - 4th International Conference on Mathematical Modelling and Computer Simulation* (pp. 60–64).

Al-Janan, D. H., & Liu, T. K. (2016). Path optimization of CNC PCB drilling using hybrid Taguchi genetic algorithm. *Kybernetes*, *45*(1), 107–125.

Alba, E. (2005). *Parallel Metaheuristics: A New Class of Algorithms*. *Parallel Metaheuristics: A New Class of Algorithms*.

Alcalá-Fdez, J., Sánchez, L., García, S., del Jesus, M. J., Ventura, S., Garrell, J. M., … Herrera, F. (2009). KEEL: a software tool to assess evolutionary algorithms for data mining problems. *Soft Computing*, *13*, 307–318.

Applegate, D. L., Bixby, R. E., Chvátal, V., Cook, W., Espinoza, D. G., Goycoolea, M., & Helsgaun, K. (2009). Certification of an optimal TSP tour through 85,900 cities. *Operations Research Letters*, *37*, 11–15.

Assad, A., & Deep, K. (2018). A hybrid Harmony Search and Simulated Annealing algorithm for continuous optimization. *Information Sciences*, *450*, 246–266.

Atashpaz-Gargari, E., & Lucas, C. (2007). Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In *2007 IEEE*

Congress on Evolutionary Computation, CEC 2007 (pp. 4661–4667).

Auger, F., Hilairet, M., Guerrero, J. M., Monmasson, E., Orlowska-Kowalska, T., & Katsura, S. (2013). Industrial applications of the kalman filter: A review. *IEEE Transactions on Industrial Electronics*, *60*(12), 5458–5471.

Bastos Filho, C. J. A., de Lima Neto, F. B., Lins, A. J. C. C., Nascimento, A. I. S., & Lima, M. P. (2008). A novel search algorithm based on fish school behavior. In *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics* (pp. 2646–2651).

Beheshti, Z., Mariyam, S., & Shamsuddin, H. (2013). A Review of Population-based Meta-Heuristic Algorithm. *Int. J. Advance. Soft Comput. Appl*, *5*(1), 2074–8523.

Beyer, H.-G., & Schwefel, H.-P. (2002). Evolution strategies – A comprehensive introduction. *Natural Computing*, *1*, 3–52.

Blum, C., & Roli, A. (2008). Hybrid metaheuristics: An introduction. In C. Blum, M. J. B. Aguilera, A. Roli, & M. Sampels (Eds.), *Studies in Computational Intelligence* (pp. 1–30). Springer, Berlin, Heidelberg.

Bottou, L., Curtis, F. E., & Nocedal, J. (2018). Optimization Methods for Machine Learning. *SIAM Review*, *60*(2), 223–311.

Boussaïd, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *Information Sciences*, *237*, 82–117.

Burke, E., Kendall, G., Newall, J., Hart, E., Schulenburg, S., & Ross, P. (2003). Hyper-Heuristics: An emerging direction in modern search technology. In F. Glover & G. A. Kochenberger (Eds.), *Handbook of Metaheuristics* (pp. 457–474). Springer, Boston, MA.

Chen, C. S., & Sun, Y. T. A. (2017). Intelligent Computer-aided Process Planning of Multi-axis CNC Tapping Machine. *IEEE Access*, *5*, 2913–2920.

Chen, S. Y. (2012). Kalman filter for robot vision: A survey. *IEEE Transactions on Industrial Electronics*, *59*(11), 4409–4420.

Chen, X., & Xu, B. (2017). Teaching-Learning-based Artificial Bee Colony. In *Advances in Swarm Intelligence* (Vol. 10385, pp. 166–178). Springer International Publishing.

Cheng, M. Y., & Prayogo, D. (2014). Symbiotic Organisms Search: A new metaheuristic optimization algorithm. *Computers and Structures*, *139*, 98–112.

Chu, S.-C., Tsai, P.-W., & Pan, J.-S. (2006). Cat Swarm Optimization. In Q. Yang & G. Webb (Eds.), *PRICAI 2006: Trends in Artificial Intelligence* (pp. 854–858). Springer, Berlin, Heidelberg.

Civicioglu, P. (2013). Backtracking Search Optimization Algorithm for numerical optimization problems. *Applied Mathematics and Computation*, *219*, 8121–8144.

Cui, L., Li, G., Zhu, Z., Ming, Z., Wen, Z., & Lu, N. (2018). Differential evolution algorithm with dichotomy-based parameter space compression. *Soft Computing*, 1–18.

Daadoo, M. (2016). Path Optimization For Computer Numerical Control-Printed Circuit Boards In Holes Drilling Process-Case Study. *International Journal of Engineering and Technology*, *6*(10), 365–377.

Daadoo, M., Eleyan, D., Tarapiah, S., Atalla, S., & Eleyan, A. (2018). Computer Numerical Control-PCB Drilling Machine with Efficient Path Planning-Case Study 2 1. *Automatic Control and Computer Sciences*, *52*(5), 451–463.

Darwin, C. (1859). *On the origin of species*. New York: D. Appleton and Company.

Das, S., Biswas, A., Dasgupta, S., & Abraham, A. (2009). Bacterial Foraging Optimization Algorithm : Theoretical foundations , analysis , and applications. In A. Abraham, A. E. Hassanien, P. Siarry, & A. P. Engelbrecht (Eds.), *Foundations of Computational Intelligence* (Vol. 3, pp. 23–55). Springer, Berlin, Heidelberg.

Derrac, J., García, S., Molina, D., & Herrera, F. (2011). A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm and Evolutionary Computation*, *1*, 3–18.

Dewil, R., Küçükoğlu, İ., Luteyn, C., & Cattrysse, D. (2018). A Critical Review of Multi-hole Drilling Path Optimization. *Archives of Computational Methods in Engineering*, *3456789*, 1–11.

Dorigo, M., Birattari, M., & Stutzle, T. (2006). Ant colony optimization. *IEEE Computational Intelligence Magazine*, *11*, 28–39.

Drias, H., Sadeg, S., & Yahi, S. (2005). LNCS 3512 - Cooperative Bees Swarm for Solving the Maximum Weighted Satisfiability Problem. In J. Cabestany, A. Prieto,

& F. Sandoval (Eds.), *Computational Intelligence and Bioinspired Systems* (Vol. 3512, pp. 318–325). Springer, Berlin, Heidelberg.

Duong, P. L. T., & Raghavan, N. (2018). Heuristic Kalman optimized particle filter for remaining useful life prediction of lithium-ion battery. *Microelectronics Reliability*, *81*, 232–243.

Eldos, T., Kanan, A., Nazih, W., & Khatatbih, A. (2015). Adapting the chemical reaction optimization algorithm to the printed circuit board drilling problem. *International Journal of Computer and Information Technology*, *9*(1), 247–252.

Eskandar, H., Sadollah, A., Bahreininejad, A., & Hamdi, M. (2012). Water cycle algorithm - A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Computers and Structures*, *110*(111), 151–166.

Farswan, P., & Bansal, J. C. (2018). Fireworks-inspired biogeography-based optimization. *Soft Computing*, 1–25.

Fister, I. J., Mlakar, U., Brest, J., & Fister, I. (2016). A new population-based nature-inspired algorithm every month: Is the current era coming to the end? In *StuCoSReC: proceedings of the 2016 3rd Student Computer Science Research Conference. Koper: University of Primorska* (pp. 33–37).

Fister, I. J., Yang, X. S., Fister, I., Brest, J., & Fister, D. (2013). A brief review of nature-inspired algorithms for optimization. *Elektrotehniski Vestnik/Electrotechnical Review*, *80*(3), 116–122.

Fogel, D. B., & Fogel, L. J. (1996). An introduction to evolutionary programming. In J. M. Alliot, E. Lutton, E. Ronald, M. Schoenauer, & D. Snyers (Eds.), *Artificial Evolution* (pp. 21–33). Springer, Berlin, Heidelberg.

Gandomi, A. H., & Alavi, A. H. (2012). Krill herd: A new bio-inspired optimization algorithm. *Communications in Nonlinear Science and Numerical Simulation*, *17*, 4831–4845.

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Comput . & Ops . Res*, *13*(5), 533–549.

Gogna, A., & Tayal, A. (2013). Metaheuristics: Review and application. *Journal of Experimental and Theoretical Artificial Intelligence*, *25*(4), 503–526.

Goudos, S. K., Baltzis, K. B., Antoniadis, K., Zaharis, Z. D., & Hilas, C. S. (2011). A comparative study of common and self-adaptive Differential Evolution strategies on numerical benchmark problems. *Procedia Computer Science*, *3*, 83–88.

Greiner, D., Periaux, J., Quagliarella, D., Magalhaes-mendes, J., & Galván, B. (2018). Evolutionary Algorithms and Metaheuristics: Applications in Engineering Design and Optimization. *Mathematical Problems in Engineering*, 1–4.

Grewal, M. S., & Andrews, A. P. (2010). Applications of Kalman filtering in aerospace 1960 to the present [historical perspectives]. *IEEE Control Systems*, *30*(3), 69–78.

Gutjahr, W. J. (2010). Convergence Analysis of Metaheuristics. In V. Maniezzo, T. Stutzle, & S. Voß (Eds.), *Matheuristics. Annals of Information Systems* (Vol. 10, pp. 159–187). Springer, Boston, MA.

Hatamlou, A. (2013). Black hole: A new heuristic optimization approach for data clustering. *Information Sciences*, *222*, 175–184.

Helsgaun, K. (2000). Effective implementation of the Lin-Kernighan traveling salesman heuristic. *European Journal of Operational Research*, *126*, 106–130.

Holland, J. H. (1992). Genetic Algorithms. *Scientific American*, 66–72.

Hultmann Ayala, H. V., dos Santos Coelho, L., & Reynoso-Meza, G. (2017). Heuristic Kalman Algorithm for Multiobjective Optimization. *IFAC-PapersOnLine*, *50*(1), 4460–4465.

Iberahim, F., Ramli, R., Narooei, K. D., & Qudeiri, J. A. (2014). Tool path optimization for drilling process by CNC milling machine using Ant Colony Optimization (ACO). *Australian Journal of Basic and Applied Sciences*, *8*(19), 106–110.

Ismail, M. M., Othman, M. A., Sulaiman, H. A., Misran, M. H., Ramlee, R. H., Abidin, A. F. Z., … Yakop, F. (2012). Firefly algorithm for path optimization in PCB holes drilling process. *Proceedings of the 2012 International Conference in Green and Ubiquitous Technology, GUT 2012*, 110–113.

Jamil, M., & Yang, X.-S. (2013). A Literature Survey of Benchmark Functions For Global Optimization Problems. *International Journal of Mathematical Modelling and Numerical Optimisation*, *4*(2), 150–194.

Jiang, Q., Zhang, Y.-D., Yang, J., Wang, L., Liu, S., Li, W., & Wang, B. (2018). An adaptive encoding learning for artificial bee colony algorithms. *Journal of*

Computational Science, *30*, 11–27.

Kakandikar, G. M., & Nandedkar, V. M. (2018). Engineering Optimization. In *Sheet Metal Forming Optimization* (pp. 45–59). CRC Press.

Kallioras, N. A., Lagaros, N. D., & Avtzis, D. N. (2018). Pity beetle algorithm – A new metaheuristic inspired by the behavior of bark beetles. *Advances in Engineering Software*, *121*, 147–166.

Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Transaction of the SME-Journal of Basic Engineering*, *82*(Series D), 35–45.

Kanagaraj, G., Ponnambalam, S. G., & Lim, W. C. E. (2014). Application of a hybridized cuckoo search-genetic algorithm to path optimization for PCB holes drilling process. In *IEEE International Conference on Automation Science and Engineering* (pp. 373–378). IEEE.

Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *Journal of Global Optimization*, *39*, 459–471.

Kaveh, A., & Farhoudi, N. (2013). A new optimization method: Dolphin echolocation. *Advances in Engineering Software*, *59*, 53–70.

Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. In *Neural Networks, 1995. Proceedings., IEEE International Conference on* (pp. 1942–1948).

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by Simulated Annealing. *Science, New Series*, *220*(4598), 671–680.

Klein, C. E., & Coelho, L. dos S. (2018). Meerkats-inspired Algorithm for global optimization problems. In *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.* (pp. 679–684).

Klein, C. E., Mariani, V. C., & Coelho, L. dos S. (2018). Cheetah Based Optimization Algorithm: A Novel Swarm Intelligence Paradigm. In *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.* (pp. 685–690).

Kolahan, F., & Liang, M. (1996). A tabu search approach to optimization of drilling operations. *Computers & Industrial Engineering*, *31*(1/2), 371–374.

Koza, J. R., & Edu, K. S. (1990). *Genetic Programming: A paradigm for genetically breeding populations of computer programs to solve problems*.

Kuo, H. C., & Lin, C. H. (2013). Cultural Evolution Algorithm for Global Optimizations and its Applications. *Journal of Applied Research and Technology*, *11*(4), 510–522.

Kwon, W. H., Kim, P. S., & Han, S. H. (2002). A receding horizon unbiased FIR filter for discrete-time state space models. *Automatica*, *38*, 545–551.

Leon, M., & Xiong, N. (2018). Enhancing adaptive Differential Evolution algorithms with rank-based mutation adaptation. In *2018 IEEE Congress on Evolutionary Computation, CEC 2018 - Proceedings* (pp. 1–7). IEEE.

Liang, J. J., Qu, B. Y., & Suganthan, P. N. (2013). *Problem Definitions and Evaluation Criteria for the CEC 2014 Special Session on Constrained Real-Parameter Optimization*. *Technical Report 201311*. Zhengzhou, China.

Lim, W. C. E., Kanagaraj, G., & Ponnambalam, S. G. (2014). PCB drill path optimization by combinatorial cuckoo search algorithm. *The Scientific World Journal*, *2014*, 1–22.

Liu, Q., Wu, L., Xiao, W., Wang, F., & Zhang, L. (2018). A novel hybrid bat algorithm for solving continuous optimization problems. *Applied Soft Computing Journal*, *73*, 67–82.

Manda, K., Chandra Satapathy, S., & Poornasatyanarayana, B. (2012). Population based meta-heuristic techniques for solving optimization problems: A selective survey. *International Journal of Emerging Technology and Advanced Engineering Website: Www.Ijetae.Com*, *2*(11), 206–211.

Mavrovouniotis, M., Li, C., & Yang, S. (2017). A survey of swarm intelligence for dynamic optimization: Algorithms and applications. *Swarm and Evolutionary Computation*, *33*, 1–17.

Mehrjou, A., & Schölkopf, B. (2018). Deep nonlinear non-gaussian filtering for dynamical systems. In *Conference on Neural Information Processing Systems (NIPS 2018)* (pp. 1–6).

Merchant, M. E. (1985). World trends and prospects in manufacturing technology. *International Journal of Vehicle Design*, *6*(2), 121–138.

Mladenovic, N., & Hansen, P. (1997). Variable Neighborhood Search. *Computers & Operations Research*, *24*(11), 1097–1100.

Nabeel Kadim, A. A.-S., & Hassan Fahad, A. (2014). Tool Path Optimization of Drilling Sequence in CNC Machine Using Genetic Algorithm. *Innovative Systems Design and Engineering*, *5*(1), 15–26.

Nobahari, H., & Sharifi, A. (2019). A hybridization of extended Kalman filter and Ant Colony Optimization for state estimation of nonlinear systems. *Applied Soft Computing Journal*, *74*, 411–423.

Ojstersek, R., Zhang, H., Liu, S., & Buchmeister, B. (2018). Improved Heuristic Kalman Algorithm for Solving Multi-Objective Flexible Job Shop Scheduling Problem. In *28th International Conference on Flexible Automation and Intelligent Manufacturing* (Vol. 17, pp. 895–902). Elsevier B.V.

Ojstersek, R., Zhang, H., Palcic, I., & Buchmeister, B. (2017). Use of Heuristic Kalman Algorithm for JSSP. In *XVII International Scientific Conference on Industrial Systems* (pp. 72–77).

Oliva, D., Hinojosa, S., & Demeshko, M. V. (2017). Engineering applications of metaheuristics: An introduction. *Journal of Physics: Conference Series*, *803*(1–11).

Omar, N., Eng, C. O., Adam, A., Hasim, S. H., Zainal Abidin, A. F., Jaafar, H. I., … Osman, K. (2014). An Experimental Study of the Application of Gravitational Search Algorithm in Solving Route Optimization Problem for Holes Drilling Process. In *International Conference Recent Treads in Engineering and Technology* (pp. 7–10).

Osman, I. H., & Kelly, J. P. (1997). Meta-Heuristics Theory and Applications. *Journal of the Operational Research Society*, *48*, 657–657.

Othman, M. H., Abidin, A. F. Z., Adam, A., Yusof, Z. M., Ibrahim, Z., Mustaza, S. M., & Lai, Y. Y. (2011). A Binary Particle Swarm Optimization Approach for Routing in PCB Holes Drilling Process. *1st International Conference on Robotic Automation System*, *2*, 201–206.

Pakrashi, A. (2015). A new hybrid clustering approach based on heuristic Kalman algorithm. In B. K. Panigrahi, P. Suganthan, & S. Das (Eds.), *Swarm, Evolutionary, and Memetic Computing* (Vol. 8947, pp. 445–455). Springer, Cham.

Pakrashi, Arjun, & Chaudhuri, B. B. (2016). A Kalman filtering induced heuristic optimization based partitional data clustering. *Information Sciences*, *369*, 704–717.

Piotrowski, A. P., Napiorkowski, M. J., Napiorkowski, J. J., & Rowinski, P. M. (2017). Swarm Intelligence and Evolutionary Algorithms: Performance versus speed. *Information Sciences*, *384*, 34–85.

Premaratne, U., Samarabandu, J., & Sidhu, T. (2009). A new biologically inspired optimization algorithm. In *ICIIS 2009 - 4th International Conference on Industrial and Information Systems 2009, Conference Proceedings* (pp. 279–284).

Raidl, G. R., Puchinger, J., & Blum, C. (2019). Metaheuristic hybrids. In *International Series in Operations Research and Management Science* (pp. 385–417). Springer New York LLC.

Ramos, V., Fernandes, C., & Rosa, A. C. (2005). Social cognitive maps, swarm collective perception and distributed search on dynamic landscapes. *Journal of New Media in Neural and Cognitive Science*, 1–24.

Rashedi, E., Nezamabadi-pour, H., & Saryazdi, S. (2009). GSA: A Gravitational Search Algorithm. *Information Sciences*, *179*, 2232–2248.

Ren, Z., Liang, Y., Wang, L., Zhang, A., Pang, B., & Li, B. (2018). Anisotropic adaptive variance scaling for Gaussian estimation of distribution algorithm. *Knowledge-Based Systems*, *146*, 142–151.

Ryan, C., Collins, J., & Neill, M. 0. (1998). Grammatical Evolution : Evolving Programs for an Arbitrary Language. *Genetic Programming. EuroGP 1998. Lecture Notes in Computer Science*, *1391*, 83–96.

Saelal, M. S., Abidin, A. F. Z., Adam, A., Mukred, J. A. A., Khalil, K., Yusof, Z. M., … Nordin, N. A. (2012). An Ant Colony System for Routing in PCB Holes Drilling Process. *The International Symposium on Innovative Management Information Production*, *3*(1), 50–56.

Sai, V.-O., Shieh, C.-S., Lin, Y.-C., Horng, M.-F., Nguyen, T.-T., Le, Q.-D., & Jiang, J.-Y. (2016). Comparative Study on Recent Development of Heuristic Optimization Methods. In *Proceedings - 2016 3rd International Conference on Computing Measurement Control and Sensor Network, CMCSN 2016* (pp. 68–71).

Schon, T., Gustafsson, F., & Hansson, A. (2003). A note on state estimation as a convex optimization problem. In *IEEE International Conference on Acoustics, Speech and Signal Processing* (pp. 61–64).

Simon, D. (2008). Biogeography-based optimization. *IEEE Transactions on Evolutionary Computation*, *12*(6), 702–713.

Sörensen, K. (2015). Metaheuristics-the metaphor exposed. *International Transactions in Operational Research*, *22*, 3–18.

Sörensen, K., Sevaux, M., & Glover, F. (2018). A History of Metaheuristics. In R. Marti, P. Panos, & M. Resende (Eds.), *Handbook of Heuristics* (pp. 1–18). Springer, Cham.

Srivastava, P. R. (2015). A cooperative approach to optimize the Printed Circuit Boards drill routing process using Intelligent Water Drops. *Computers and Electrical Engineering*, *43*, 270–277.

Srivatsan, R. A., & Choset, H. (2016). Multiple Start Branch and Prune Filtering Algorithm for Nonconvex Optimization. In *The 12th International Workshop on the Algorithmic Foundations of Robotics* (pp. 1–16).

Storn, R., & Price, K. (1997). Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces. *Journal of Global Optimization*, *11*, 341–359.

Suganthan, P. N. (2013). Shared Documents - cec14-matlab-code.zip. Retrieved January 21, 2018, from http://web.mysites.ntu.edu.sg/epnsugan/PublicSite/Shared Documents/AllItems.aspx

Talbi, E. G. (2009). *Metaheuristics: From Design to Implementation*. *Metaheuristics: From Design to Implementation*. John Wiley & Sons, Inc., Hoboken, New Jersey.

Tanabe, R., & Fukunaga, A. S. (2014). Improving the search performance of SHADE using linear population size reduction. In *Proceedings of the 2014 IEEE Congress on Evolutionary Computation, CEC 2014* (pp. 1658–1665).

Teodorović, D., & Dell 'orco, M. (2015). Bee Colony Optimization – A cooperative learning approach to complex transportation problems. *Advanced OR and AI Methods in Transportation*, 51–60.

Toscano, R., & Lyonnet, P. (2009). *Mixed H2/H∞residual generator design via Heuristic Kalman Algorithm*. *IFAC Proceedings Volumes (IFAC-PapersOnline)* (Vol. 42). IFAC. https://doi.org/10.3182/20090630-4-ES-2003.0022

Toscano, R., & Lyonnet, P. (2010). A new heuristic approach for non-convex optimization problems. *Information Sciences*, *180*(10), 1955–1966. https://doi.org/10.1016/j.ins.2009.12.028

Toscano, Rosario. (2013). Heuristic Kalman algorithm. In *Advances in Industrial Control* (pp. 107–128). https://doi.org/10.1007/978-1-4471-5188-3_5

Toscano, Rosario, & Ivan, I. A. (2014). Robust structured controllers for piezoelectric microactuators. *ISA Transactions*, *53*(6), 1857–1864. https://doi.org/10.1016/j.isatra.2014.08.009

Toscano, Rosario, & Lyonnet, P. (2009a). Heuristic kalman algorithm for solving optimization problems. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*. https://doi.org/10.1109/TSMCB.2009.2014777

Toscano, Rosario, & Lyonnet, P. (2009b). Robust PID controller tuning based on the heuristic Kalman algorithm. *Automatica*, *45*(9), 2099–2106. https://doi.org/10.1016/j.automatica.2009.05.007

Toscano, Rosario, & Lyonnet, P. (2012). A Kalman optimization approach for solving some industrial electronics problems. *IEEE Transactions on Industrial Electronics*, *59*(11), 4456–4464. https://doi.org/10.1109/TIE.2011.2169637

Voß, S. (2001). Meta-heuristics: The State of the Art. In *Local Search for Planning and Scheduling. LSPS 2000. Lecture Notes in Computer Science* (pp. 1–23). Springer, Berlin, Heidelberg.

Wang, Y., & Chaib-draa, B. (2012). An adaptive nonparametric particle filter for state estimation. In *2012 IEEE International Conference on Robotics and Automation* (pp. 4355–4360). IEEE.

Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, *1*(1), 67–82.

Yang, J. (2018). Remaining Useful Life Assessment of Lithium-ion Battery based on HKA-ELM Algorithm. *International Journal of Electrochemical Science*, *13*, 9257–9272.

Yang, X.-S. (2010). Firefly Algorithm, Stochastic Test Functions and Design Optimisation. *Int. J. Bio-Inspired Computation*, *2*(2), 78–84.

Yang, X.-S., & Deb, S. (2009). Cuckoo Search via Lévy Flights. In *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC 2009)* (pp. 210–

214).

Yang, X. S. (2012). Flower pollination algorithm for global optimization. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 240–249).

Yufa, X., Chen, G., & Jinshou, Y. (2006). The Kalman Particle Swarm Optimization Algorithm and Its Application in Soft-sensor of Acrylonitrile Yield. In *2005 International Conference on Neural Networks and Brain* (pp. 124–127). IEEE.

Zhang, J., Xiao, M., Gao, L., & Pan, Q. (2018). Queuing search algorithm: A novel metaheuristic algorithm for solving engineering optimization problems. *Applied Mathematical Modelling*, *63*, 464–490.

Zhang, Q., Wang, R., Yang, J., Lewis, A., Chiclana, F., & Yang, S. (2018). Biology migration algorithm: a new nature-inspired heuristic methodology for global optimization. *Soft Computing*, 1–26.

Zhang, W. B., & Zhu, G. Y. (2018). Drilling Path Optimization by Optimal Foraging Algorithm. *IEEE Transactions on Industrial Informatics*, *14*(7), 2847–2856.

Zhang, X., Kang, Q., Cheng, J., & Wang, X. (2018). A novel hybrid algorithm based on Biogeography-Based Optimization and Grey Wolf Optimizer. *Applied Soft Computing Journal*, *67*, 197–214.

Zhu, G. Y. (2006). Drilling path optimization based on swarm intelligent algorithm. In *2006 IEEE International Conference on Robotics and Biomimetics, ROBIO 2006* (pp. 193–196).

Zhu, G. Y., & Zhang, W. B. (2008). Drilling path optimization by the particle swarm optimization algorithm with global convergence characteristics. *International Journal of Production Research*, *46*(8), 2299–2311.