

ASSEMBLY SEQUENCE PLANNING USING HYBRID
BINARY PARTICLE SWARM OPTIMIZATION

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Electrical Engineering)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

DECEMBER 2014

Dedicated, in thankful appreciation to my father, who loved me and did not only raise and nurture me but also taxed himself dearly over the years for my education and intellectual development.

Dedicated to my mother, who has been a source of endless love, motivation and strength during moments of despair and discouragement.

Dedicated to my brothers Wadee and Aref to my sisters Manal and Nawal, for their endless love, and spiritual support.

Dedicated to my lovely wife Norshifah for her endless love, care, motivation and understanding.

To my kids Fatihah, Luqman, Syabaan, Daniel, Nibras and Wardah for their love and motivation.

ACKNOWLEDGEMENT

I would like to thank Almighty Allah for His Greatness and Mercy, for giving me the strength, patience and chance to be in UTM, completing this thesis.

I am using this opportunity to express my gratitude to everyone who supported me throughout this PhD thesis. I would like to express my utmost appreciation to Prof Dato' Seri Ir. Dr Zaini Ujang the fifth Vice-Chancellor of University Technology Malaysia (October 2008 – May 2013) for his support and understanding to make this work to finish with the least suffer.

Appreciation to the former FKE dean Prof. Dato' Dr. Ahmad Bin Darus for his strong support, encouragements and believe in my capabilities. Much appreciation goes to Prof. Shamsuddin Hj. Mohd Amin for his valuable guidance, unlimited support, and encouragement for publication.

Appreciation to my supervisor PM. Dr. Rosbi Bin Mamat, and to my two co-supervisors Prof. Dr. Siti Mariyam Shamsuddin, and PM. Dr. Zuwairie Bin Ibrahim for their guidance, encouragement, and understanding.

ABSTRACT

Assembly Sequence Planning (ASP) is known as a large-scale, time-consuming combinatorial problem. Therefore time is the main factor in production planning. Recently, ASP in production planning had been studied widely especially to minimize the time and consequently reduce the cost. The first objective of this research is to formulate and analyse a mathematical model of the ASP problem. The second objective is to minimize the time of the ASP problem and hence reduce the product cost. A case study of a product consists of 19 components have been used in this research, and the fitness function of the problem had been calculated using Binary Particle Swarm Optimization (BPSO), and hybrid algorithm of BPSO and Differential Evolution (DE). The novel algorithm of BPSODE has been assessed with performance-evaluated criteria (performance measure). The algorithm has been validated using 8 comprehensive benchmark problems from the literature. The results show that the BPSO algorithm has an improved performance and can reduce further the time of assembly of the 19 parts of the ASP compared to the Simulated Annealing and Genetic Algorithm. The novel hybrid BPSODE algorithm shows a superior performance when assessed via performance-evaluated criteria compared to BPSO. The BPSODE algorithm also demonstrated a good generation of the recorded optimal value for the 8 standard benchmark problems.

ABSTRAK

Perancangan Jujukan Pemasangan (ASP) dikenali sebagai masalah kombinatorik berskala besar yang memakan masa. Oleh itu masa adalah faktor utama dalam perancangan pengeluaran. Baru-baru ini, ASP dalam perancangan pengeluaran telah dikaji secara meluas terutamanya untuk meminimumkan masa dan seterusnya mengurangkan kos. Objektif pertama penyelidikan ini ialah merumus and menganalisa model matematik bagi masalah ASP. Objektif kedua ialah untuk meminimumkan masa bagi masalah ASP dan seterusnya mengurangkan kos produk. Satu kajian kes bagi satu produk yang terdiri dari 19 komponen telah digunakan di dalam penyelidikan ini, dan algoritma *Particle Swarm Optimization* (BPSO) serta algoritma hibrid yang terdiri dari BPSO dan *Differential Evolution* (DE) telah diguna untuk mengira fungsi kecergasan bagi masalah ASP tersebut. Algoritma baru BPSODE dinilai menggunakan kriteria ukuran prestasi. Algoritma BPSODE ini disahkan dengan menggunakan 8 masalah penanda aras yang komprehensif yang ada di dalam literatur. Keputusan menunjukkan bahawa algoritma BPSO mempunyai prestasi yang lebih baik dan boleh mengurangkan lagi masa pemasangan bagi ASP dengan 19 bahagian berbanding dengan algoritma *Simulated Annealing* dan *Genetic Algorithm*. Algoritma hibrid baru BPSODE menunjukkan prestasi yang cemerlang berbanding dengan BPSO apabila dinilai menggunakan kriteria ukuran prestasi. Algoritma BPSODE juga menunjukkan penjanaan nilai rakaman optimum yang bagus bagi 8 masalah penanda aras piawai.

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LIST OF ABBREVIATIONS

ASP	-	Assembly Sequence Planning.
PSO	-	Particle Swarm Optimization.
BPSO	-	Binary Particle Swarm Optimization.
DE	-	Differential Evolution.
BPSODE	-	Binary Particle Swarm Optimization Differential Evolution.
SA	-	Simulated Annealing.
GA	-	Genetic Algorithm.
CAD	-	Computer Aided Design.
NP	-	Nondeterministic Polynomial.
ASTD	-	Assembly State Transition Diagram.
AFI	-	Assembly From Industry.
PCB	-	Printed Circuit Board.
AC	-	Ant Colony.
NN	-	Neural Networks.
EA	-	Evolutionary Algorithm.
GP	-	Genetic Programming.
EP	-	Evolutionary Programming.
ES	-	Evolutionary Strategies.
OGA	-	Ordering Genetic Algorithm.
ALB	-	Assembly Line Balancing.
GSAA	-	Genetic Simulated Annealing Algorithm.
DPSO	-	Discrete Particle Swarm Optimization.
SI	-	Swarm Intelligence.
TSP	-	Travelling Sales Problem.
DEPSO	-	Differential Evolution Particle Swarm Optimization.

BBDE	-	Bare Bones Differential Evolution.
BPSODE	-	Binary Particle Swarm Optimization Differential Evolution.
PS	-	Pattern Search.
LUS	-	Local Unimodal Sampling.
MOL	-	Many Optimizing Liaisons.
GD	-	Gradient Descent.
FCT	-	Factory Capacity Table.
APM	-	Assembly Precedence Matrix .
OCC	-	Operator Choice Complexity.
CR	-	Crossover.
T	-	Tool changing.
AMOPSO	-	Another Multi-Objective Particle Swarm Optimization.
VEPSO	-	Vector Evaluated Particle Swarm Optimization.
ADI	-	After Diversity Improvement.
SR	-	Success Rate.
AE	-	Average Error.
ACT	-	Average Computational Time.
<i>Eff.</i>	-	Efficiency.
SQ	-	Solution Quality.
SD	-	Standard Deviation.
BFA	-	Best Fitness Accuracy.

LIST OF SYMBOLS

i^{th}	-	i^{th} particle
X_i	-	i^{th} particle is represented by d^{th} dimensional vector
pop	-	The swarm size of n particle are named population
PB_i	-	The individual best position fitness value
GB	-	The swarm global best position
V_i	-	The particle velocity is the rate of change of position
$v_{i,d}^{k+1}$	-	Velocity of i^{th} particle at iteration $k+1$ and d^{th} dimension
$x_{i,d}^{k+1}$	-	Position at i^{th} particle, iteration $k+1$ and d^{th} dimension
$v_{i,d}^k$	-	Velocity of i^{th} particle at iteration k and d^{th} dimension
$pbest_{i,d}^k$	-	The individual best position at iteration k and d^{th} dimension
$gbest_{i,d}^k$	-	The swarm global best position at iteration k and d^{th} dimension
$x_{i,d}^k$	-	Position at i^{th} particle, iteration k and d^{th} dimension
w	-	Inertia weight
$rand_1$	-	Random value from 0 to 1
$rand_2$	-	Random value from 0 to 1
c_1	-	Cognitive factor
c_2	-	Social factor
d	-	d^{th} dimension of the search space
k	-	k^{th} iteration
PM	-	The Precedence Matrix
FA	-	The Feasible sequence Assembly
Ω	-	Group of parts that assembled earlier than part (j)
part (i)	-	Part to be assembled

part (j)	-	Part already assembled
part (i)	-	a predecessor of part (j)
$n!$	-	'n' factorial
$T_{Setup}(i)$	-	The time of <i>setup</i>
P_{io}	-	Setup time for product i being the first component in the assembly
P_{ij}	-	Contribution to the setup time due to the presence of part j when entering part i
A_i	-	Assembly time for component <i>i</i> .
$Min T_{Assembly}$	-	The optimum assembly time
R_j	-	Reorientation
$\forall_{i,j}$	-	For all parts
Z_1	-	Assembly objective function
T_i	-	Tool changing
T	-	Total number of <i>tool changing</i>
Z_1	-	Individual objective function 1
Z_2	-	Individual objective function 2
Z	-	Combination of two objective functions
$Min Z$	-	Minimization of total objective functions
w_i	-	The indicator weight of the each function
(i)	-	'i' is equal 1 or 2
$v_{ij}(t + 1)$	-	Velocity of a particle from location i to j
$V_{max j}$	-	Max. velocity at j
$c_{1,min}$	-	Min. value of cognitive function c_1
$c_{2,min}$	-	Min. value of Social function c_2
$c_{1,max}$	-	Max. value of cognitive function c_1
$c_{2,max}$	-	Max. value of Social function c_2
\vec{X}	-	System performance
\vec{X}^*	-	Best system performance evaluated by fitness function
\mathfrak{R}	-	Search space
\mathfrak{R}^D	-	Search space with D dimensional
$x_j^{(L)}$	-	Lower boundary constraint

$x_j^{(U)}$	-	Upper boundary constraint
(P)	-	Differential Evolution population
p^G	-	Differential Evolution feasible solutions
(N_p)	-	Differential Evolution constant size population N
X_i^G	-	Real valued vector; where :
(i)	-	Indexes the population
(G)	-	The generation to which the population belongs
G_{max}	-	Max. number of population in specific generation
$p^{G=0}$	-	The initial population in generation
$rand_j[0,1]$	-	Uniformly distributed random value within the range: [0.0,1.0]
p^{G+1}	-	Subsequent generation
$u_{j,i}^{G+1}$	-	Trial vector
r_1, r_2 and r_3	-	Random, integer values
$U_{i,G+1}$	-	Trial vector differs from its counterpart in previous generation, $X_{i,G}$
(F)	-	DE control real-valued parameter in binary of value '0' & '1'
(CR)	-	DE control real-valued parameter of Crossover
$sigmoid(v_{i,d}^k)$	-	Function to map velocity to a probability in the range [0, 1]

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CHAPTER 1

INTRODUCTION

1.1 Background

Assembly Sequence Planning (ASP) is a very well known problem of scheduling of the production process, which has been identified in the field of Computational Complexity Theory as a strongly Nondeterministic Polynomial time problem, and it is considered among the researchers in the field of softcomputing field as a best example of a mathematically complex problem especially when the number of components of a product increased. The essential characteristic of ASP is to find the best sequence of tasks in any assembly process in the assembly line, in order to reduce the time of putting the components together, or cut off the process cost (HongGuang, and Cong, 2010).

The three words assembly sequence planning (ASP) determines the product's parts sequence and the details of the process of the assembly operations that put together each and every individual part of the product into an assembly (Bourjault, 1984; De Fazio and Whitney, 1987; Homen de Mello and Sanderson, 1990; 1991a). The plan of the assembly has a tremendous impact on the production process

incurred due to the assembly of the product, play a very important factor in the product cost. The main contribution of this thesis is to minimize the time of assembly, which consequently will lead to a reduction of the product cost.

In assembly planning many parameters must be taken in consideration (Bourjault, 1984; De Fazio and Whitney, 1987; Homen de Mello and Sanderson, 1990; 1991a; 1991b). These parameters are important in the manufacturing process such as the physical geometric design of an assembly must be examined in prior to confirm a sequence that is feasible for assembly; that is the parts does not collide with each other or parts stacking. The assembly process would not be successful without modification to be done to the assembly process.

Assembly sequences for the components in a product that can create the complete product in practice; are those named feasible assembly sequences. Out of all feasible assembly sequences, plan for sequencing assembly is frequently reduced to search for the optimal, or a sub optimal sequence of assembly. The optimum or sub optimum sequence is the sequence with the optimum or a partial optimum for total assembly time, used resources, or combinations of these properties.

A detailed information related to the assembly process during the manufacturing operation is required in order to find the precedence relation between components, that is usually may not be available in the product model. Mainly computer tools are used to gather the relation between components, even though sometimes it could be done through interrogating a human assembly planner. The physical shape description of the assemblage will constitute the inputs to the computer tools, with some times simple interconnections amongst units. The parts interconnections are classified whether these matings are fixed or not and whether components mate with each other (Gottschlich *et al.*, 1994) provided an overview of techniques in assembly sequence planning.

A good assembly sequence can be achieved by considering few parameters such as *tool changing and tool complexity*, *reorientation*, *directionality*, *stability*, *manipulability*, and *parallelism* of assembly operations. Those factors certified a high quality sequence relating to efficient of sequence, costing, assembly safety, and safety of workers in regards to the operations (Homen de Mello and Sanderson, 1991a; Waarts *et al.*, 1992; Ben-Arieh and Kramer, 1994; Xu *et al.*, 1994; Dini and Santochi, 1992; Lee and Ko, 1987; Lin and Chang, 1991). The production engineers target is to make the assembly process more easy, and that objective can be achieved by automating the generation of the assembly process (Ben-Arieh, 1994; Shpitalni *et al.*, 1989; Lee and Shin, 1988; Bullinger and Ammer, 1984; Wolter, 1990; De Floriani, 1989;). The sequence of the assembly is the *spine* of any assembly process, in that sense, generating sequencing automatically is the main target of this research.

In this thesis, the differences between the two terms *parts* and *components* will be explained to avoid confusion, as both terms will be frequently used. A *part* constitutes the smallest unit within a product; it cannot be subdivided into smaller units. The set of parts constitutes a *component* is stable, i.e. it does not fall into pieces during assembly process. The part is also considered as component because it is always stable.

1.3 Research Objectives

The objectives of this research can be summarized as follows:

1. To formulate and analyse the Assembly Sequence Planning (ASP) model.
2. To minimize the time of assembly sequence using hybrid Binary Particle Swarm Optimization (BPSO) and Differential Evolution (DE) algorithms.
3. The algorithm will be assessed using performance-evaluated criteria, and validated via 8 standard benchmark problems from the literature.

1.4 Research methodology

To date various methods have been developed and introduced to solve the problem of assembly sequence planning (ASP), by minimizing the time of assembly and consequently reducing the cost of manufacturing. It was decided that the best method to adopt for this investigation was to hybrid a two well-known algorithms that are Binary Particle Swarm Optimization (BPSO) and Differential Evolution (DE).

A case study approach which consist of a product consist of 19 components, at which each part of the product assembly was labelled by a number from 1 to 19 without going into the physical diagram details of the product. The table of constraints that restrict the assembly of the parts will ensure the production of feasible sequences. At first a thorough analysis to the formulated ASP model will be performed and the formula would be modified in order to use it in the algorithms of optimization to search for the minimum time of sequences assembly of the product. Any sequences that did not follow strictly the rules of the assembly constraints will be considered as infeasible sequences and should be discarded. The search for feasible sequences will be attchieved by implementing a meta-heuristic algorithm known as binary particle swarm optimization (BPSO). The global best optimum value obtained by the BPSO algorithm will be used as an input to the differential evolution algorithm (DE) to obtain the best minimum value of time.

A standard performance measures from literature will be used to evaluate the efficiency and performance of the hybrid algorithm (BPSODE) compared to Simulated Annealing (SA) and Genetic algorithm (GA) that been used to solve the ASP problem. The algorithm will be validated by using the hybrid algorithm (BPSODE) to solve eight standard problems from the literature.

1.5 Research scope and limitation

1. The investigation is performed on an assembly product from industry that its components to be assembled were labelled by numbers instead of real pictures of the product (Motavalli, S. Islam, A. 1997; Choi *et al.*, 2009).
2. Optimization of the time of total assembly sequences and the total number of tool changing will be considered.
3. The constraints of the assembly design are the precedence relationships between the components subjected to the assembly process.
4. Eight Benchmark functions widely used in the literature will be implemented to validate the algorithm.
5. The programming language implemented is Matlab and Delfi.

1.6 Thesis organization

Chapter 1 provides a brief overview of the assembly sequence planning problem and the previous work done to solve it. The importance of the assembly part of the manufacturing was highlighted, as well the factors that have to be taken strictly into consideration in order to obtain a feasible sequences. Good feasible sequences leads to a minimum value of time of assembly and accordingly reduction of the cost of the manufacturing process. The research scope and limitation were introduced to bring a clear idea about the strength and weaknesses of the research.

Chapter 2 introduced the nature of the ASP problem and the different techniques that have been used by different researchers to tackle the problem. It clarify how the assembly sequences is more difficult than finding disassembly sequences. It introduced briefly the assembly modeling, using CAD and the functional precedence constraints amongst the connections, the exact method used after that, and then provides an overview of the stochastic techniques used, and the meta-heuristic methods implemented to solve ASP.

Chapter 3 explained in more details the methodology implemented in order to solve the ASP problem. First the ASP problem was formulated and analysed mathematically, and the strategies implemented to diversify the feasible sequences obtained by the searching algorithms. The case study used, that consist of 19 components and the parameters that considered, such as the precedence constraints and the coefficient table data implemented. A detailed overview of the particle swarm optimization (PSO), the binary PSO, the differential evolution (DE) and the proposed hybrid method that labelled as (BPOSDE).

Chapter 4 discussed in details the obtained results by the research, and demonstrates the simulation graphs in conjunction with thorough analysis. The results generated by the first to implement (in this thesis); algorithm Binary PSO to solve Assembly Sequence Planning (ASP) is demonstrated, analysed thoroughly, and compared with another algorithm of Genetic Algorithm (GA) and Simulated Annealing (SA), which shows a better optimal time. The result of the novel hybrid algorithm BPSODE is introduced, and its performance-evaluated criteria are justified, and the algorithm validation is proven through the implementation of standard well known 8 benchmark problems from the literature. The novel algorithm managed to generate the benchmark problems optimum values as recorded in the literature.

Chapter 5 discussed the formula modification of the fitness function of the ASP problem by analysing the actual assembly time of a number of feasible sequences from the literature. It is also discussed the results obtained by Binary PSO in a comparison with genetic algorithm and simulated annealing algorithm in solving the ASP. This chapter discussed the investigation of the effects of the control parameter of PSO algorithm. It summarizes and reflects the major contributions of the proposed approaches BPSO and BPSODE in solving ASP. A discussion was given related to the hybrid algorithm (BPSODE) assessment using performance-evaluated criteria (performance measure), and discussed the algorithm validation by testing the BPSODE via 8 standard benchmark problems from the literature.

REFERENCES

- Akgündüz, O. S. and Tunali, S. (2010). An adaptive genetic algorithm approach for the mixed-model assembly line sequencing problem, *International Journal of Production Research* 48: 5157–5179.
- Al-kazemi, B. and Mohan, C. (2000). Multi-phase Discrete Particle Swarm Optimization. *In the Third International Workshop on Frontiers in Evolutionary Algorithms, Atlantic City, New Jersey, USA.*
- Alpay, S. (2009). Grasp with path relinking for a multiple objective sequencing problem for a mixed-model assembly line, *International Journal of Production Research* 47: 6001–6017.
- Babu, B.V., Onwubolu, G.C. (2004): *New Optimization Techniques in Engineering.* Springer, Heidelberg.
- Bäck, T. Hoffmeister, F. and Schwefel, H. (1991). A Survey of Evolution Strategies. *In Proceedings of the Fourth International Conference on Genetic Algorithms and their Applications*, 2-9.
- Bai, Y. W. Chen, Z. N. Bin, H. Z. Hun, J. (2005). An effective integration approach toward assembly sequence planning and evaluation. *Int J Adv Manuf Technol* 27(1-2): 96–105.
- Baldwin, D. Abell, T. Lui, M. De Fazio, T. and Whitney, D. (1991). An integrated computer aid for generating and evaluating assembly sequences for mechanical products. *IEEE Transactions on Robotics and Automation*, 7(1): 78-94.
- Belegundu, A. D. and Chandurupatla, T. R. (1999). Optimization concepts and applications in engineering. Chapter 3. Prentice Hall.
- Ben-Arieh, D. (1994). A methodology for analysis operation's difficulty. *International Journal of Production Research*. 32(8): 1879-1895.

- Ben-Arieh, D. and Kramer, B. (1994). Computer-aided process planning for assembly: generation of assembly operations sequence. *International Journal of Production Research*. 32(3): 643-656.
- Biswas, A. Dasgupta, S. Das, S. and Abraham, A. (2007) *A synergy of differential evolution and bacterial foraging algorithm for global optimization*. Neural Net w. World, 17(6): 607-626.
- Blesa Aguilera, M., Blum, C. Cotta, C., Fern´andez Leiva, A., Gallardo Ruiz, J. Roli, A. and Sampels, M. (2008). *Proceedings of the 5th International Workshop on Hybrid Metaheuristics (Lecture Notes in Computer Science Series 5296)*. Berlin: Springer-Verlag.
- Blesa Aguilera, M., Blum, C., Gaspero, L. Roli, A. Sampels, M. and Schaerf A. (2009). *Proceedings of the 6th International Workshop on Hybrid Metaheuristics (Lecture Notes in Computer Science Series 5818)*. Berlin: Springer-Verlag.
- Blum, C. Blesa Aguilera, M. J., Roli, A. and Sampels, M. (2008). *Hybrid Metaheuristics: An Emerging Approach To Optimization*. (Studies in Computational Intelligence Series 114). Berlin: Springer-Verlag.
- Blum, C. and Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Comput. Surv.* 35(3): 268-308.
- Broersma, Hajo (2011). Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem. Hindawi Publishing Corporation, *International Journal of Combinatorics*.
- Bonneville, F. Perrard, C. and Henrioud, J. (1995). A genetic algorithm to generate and evaluate assembly plans. *Proceeding of the IEEE Symposium on Emerging Technologies and Factory Automation 2*: 231-239.
- Bourjault, A. (1984). *Contribution à une approche methodologique de l'assemblage automatise: Elaboration automatique des sequences operatoires*. Thèse d'état, Universite de Franche-Comte Besancon, France.
- Boysen, N., Fliedner, M. and Scholl, A. (2009). Sequencing mixed-model assembly lines: Survey, classification and model critique, *European Journal of Operational Research* 192: 349-373.
- Boysen, N., Kiel, M. and Scholl, A. (2010). Sequencing mixed-model assembly lines to minimise the number of work overload situations, *International Journal of Production Research on line first*. DOI: 10.1080/00207543.2010.507607.

- Bullinger, H. J. and Ammer, E. D. (1984). Computer aided depicting of precedence diagrams - a step towards efficient planning in assembly. *Computing and Industrial Engineering*. 18(3/4): 165-169.
- Cao, P. B. Xiao, R. B. (2007). Assembly planning using a novel immune approach. *Int J Adv Manuf Technol* 31(7-8): 770-782.
- Chai-ead, N. Aungkulanon, P. and Luangpai-boon, P. (2011). Bees and Firefly Algorithms for Noisy Non-Linear Optimization Problems. Member-IAENG. *International Multi-conference of Engineers and Computer Scientists*.
- Chakraborty, (2008) U.K.: *Advances in Differential Evolution*. Springer, Berlin
- Chang, C. C. Tseng, H. E. Meng, L. P. (2009). Artificial immune systems for assembly sequence planning exploration. *Eng Appl Artif Intell* 22(8): 1218-1232.
- Chen, C. L. P. (2010). Neural Computation for Planning AND/OR Precedence-Constraints Robot Assembly Sequences. *Proc. Int. Conf. Neural Net*. 142(1): 127-142.
- Chen, R. S. Lu, K. Y. Yu, S. C. (2002). A hybrid genetic algorithm approach on multi-objective of assembly planning problem. *Eng Appl Artif Intell* 15(5): 447-457.
- Chen, S. F. Liu, Y. J. (2001). An adaptive genetic assembly sequence planner. *Int J Comput Int Manuf* 14(5): 489-500.
- Chen, Y. M. Lin, C. T. (2007). A particle swarm optimization approach to optimize component placement in printed circuit board assembly. *Int J Adv Manuf Technol*. 35: 610-620.
- Chengen, W. Hong, Y. Jiapeng, Y. *et al.*, (2011). Assembly planning system for complex product. *Computer Integrated Manufacturing Systems*, 17(5) : 952-960.
- Chinneck, J.W. and Ramadan, K. (2000). Linear Programming with Interval Coefficients. *Journal of the Operational Research Society*. 51: 209-220.
- Choi, Y. K. Lee, D. M. Cho, Y. B. (2009). An approach to multi-criteria assembly sequence planning using genetic algorithms. *Int J Adv Manuf Technol* 42 (1-2): 180-188.
- Chow, C.-k. and Tsui, H.-t. (2004). Autonomous agent response learning by a multi-species particle swarm optimization. *In Congress on Evolutionary*

- Computation (CEC'2004)*, 1:778–785, Portland, Oregon, USA, June 2004. IEEE Service Center.
- Clerc, M. (2004) Discrete particle swarm optimization, illustrated by the traveling salesman problem. In: Onwubolu GC, Babu BV (eds). *New optimization techniques in engineering*. Studies in fuzziness and soft computing. Springer, Heidelberg, 219–239
- Corne, D., Dorigo, M., Glover, F.(1999) *Part Two: Differential Evolution*. In: *New Ideas in Optimization*, 77–158. Mc Graw-Hill, New York.
- Das, S. and Suganthan, P. (2011). Differential evolution: A survey of the State-Of-The-Art. *IEEE transactions on evolutionary computation*. 15 (1): 4-31.
- Davidon, W. C. (1991). Variable metric method for minimization. *SIAM Journal on Optimization*. 1: 1-17.
- De Fazio, T. L. and Whitney, D. E. (1987). Simplified generation of all mechanical assembly sequences. *IEEE Journal of Robotics and Automation*, RA-3 (6), 640-658.
- De Floriani, G. N. (1989). A graph model for face-to-face assembly. *Proceedings of the IEEE International Conference on Robotics and Automation*. 1: 75-78.
- De Lit, P. Latinne, P. Rekiek, B. and Delchambre, A. (2001). Assembly planning with a genetic algorithm. *Int J Prod Res* .39(16): 3623– 3640.
- Deo, Shantanu Roya Javadpour, Gerald M. Knapp (2002). Multiple setup PCB assembly planning using genetic algorithm. *Computers and Industrial Engineering, Pergamon*, 42 (2002). 1-16.
- Dini, G. and Santochi, M. (1992). Automated sequencing and subassembly detection in assembly planning. *Annals CIRP*. 41(1): 1-4.
- Dini, G. Failli, F. Lazzerini, B. Marcelloni, F. (1999). Generation of optimize assembly sequence using genetic algorithms. *CIRP Ann* 48(1): 17–20.
- Dong, J., Xiao, T., Fan, S. and Qiang, L. (2002). Mixed-model assembly line sequencing with hybrid genetic algorithm and simulation, 541–545.
- Eberhart, R.C. and Kennedy, J. (2001). *Swarm Intelligent*. Morgan kaufmann.
- Engelbrecht, A. P. (2002). *Particle Swarm optimization: Pitfalls and converge aspects*. Tutorial, dept. Computer Science, University South Africa.
- Engelbrecht, A. P. (2002) *Computational Intelligence: An Introduction*. John Wiley and Sons.

- Engelbrecht, A. P. (2005). *Fundamentals of Computational Swarm Intelligents*. John Wiley and Sons.
- Erel, E. Sabuncuoglu, I. and Aksu, B. A. (2001). Balancing of U-type assembly system using simulated annealing. *Int J Prod Res.* 39(13): 3003–3015.
- Failli, F. and Dini, G. (2000). Ant colony systems in assembly planning: a new approach to sequence detection and optimization. *Proceedings of the 2nd CIRP International Seminar on Intelligent Computation in Manufacturing Engineering.* 227–232.
- Farahani, Sh. M. Abshouri, A. A. Nasiri, B. and Meybodi, M. R. (2011). A Gaussian Firefly Algorithm. *International Journal of Machine Learning and Computing*, vol. 1.
- Fengchan, W. Youzhao, S. Na, L. (2012). Multi station assembly sequence planning based on particle swarm optimization algorithm *Journal of Mechanical Engineering*, 48(9): 155-162
- Fieldsend, J. E. and Singh, S. (2002) A multi-objective algorithm based upon particle swarm optimisation, an efficient data structure and turbulence, *UK Workshop on Computational Intelligence (UKCI'02)*, Birmingham, Uk, 2nd - 4th Sep 2002.
- Fogel, L. (1994). *Evolutionary Programming in Perspective: The Top-down View. Computational Intelligence: Imitating Life*, J.M. Zurada, R. Marks II and C. Robinson, Eds., Piscataway, New Jersey, USA: IEEE Press.
- Fujimoto, H. Alauddin Ahmed and Milad Fares Sebaaly (1998). An Evolutionary and interactive Approach to Simulation of Assembly Planning in Virtual Environment. *Proc. Of the IEEE Int. Conf. on Robotics and Automation*, 187-192.
- Fujimoto, H. Sebaaly, M. F. (2000). A new sequence evaluation approach to assembly planning. *ASME J Manuf Sci Eng.* 22:198– 205.
- Fukuyama, Y. and Yoshida, H. (2001). A Particle Swarm Optimization for Reactive Power and Voltage Control in Electric Power Systems. *In Proceedings of the IEEE Congress on Evolutionary Computation.* Seoul, S. Korea, 87-93.
- Gao L, Qian WR, Li XY, Wang JF (2010) Application of memetic algorithm in assembly sequence planning. *Int J Adv Manuf Technol* 49(9–12): 1175–1184
- Gendreau, M. and Potvin, J. (2005). Metaheuristics in combinatorial optimization. *Ann. Oper. Res.* 140(1): 189–213.

- Glover, F. (1989). Tabu Search – Part I. *ORSA Journal on Computing*. 1(3): 190-206.
- Glover, F. (1990). Tabu Search – Part II. *ORSA Journal on Computing*. 2 (1): 4-32.
- Goldberg, D. (1989). *Genetic Algorithms in search, optimization and machine learning*. Addison-Wesley.
- Gottschlich, S., Ramos, C. and Lyons, D. (1994). Assembly and task planning: a taxonomy, *IEEE Robotics and Automation Magazine* 1(3): 4–12.
- Gray, P. Hart, W. Painton, L. Phillips, C. Trahan, M. and Wagner, J. A. (1997). *Survey of Global Optimization Methods*. Sandia National Laboratories.
- Guan, Q. Liu, J. H. Zhong, Y. F. (2002). A concurrent hierarchical evolution approach to assembly process planning. *Int J Prod Res* 40(14): 3357–3374.
- Guo, J. Wang, P. Cui, N (2007). Adaptive Ant Colony Algorithm for On-orbit Assembly Planning. *Second IEEE Conf. on Industrial Electronics and Applications* (2007), 1590-1593.
- Guo, Y. W. Li, W. D. Mileham, A. R. (2009). Applications of particle swarm optimization in integrated process planning and scheduling. *Robotics and Computer-Integrated Manufacturing* 25: 280-288.
- Gupta, S. and Krishnan V. (1998). Product family-based assembly sequence design methodology. *IEEE transactions*. 30: 933-945.
- Han, J. Wang, P. Yang, X. (2012). Tuning of PID controller based on fruit fly optimization algorithm. *International Conference on Mechatronics and Automation* (ICMA), 409-413.
- Hao, Z-F. Gua, G-H. Huang, H. (2007). A Particle Swarm Optimization Algorithm with Differential Evolution. *Sixth International conference on Machine Learning and Cybernetics*, 1031 – 1035.
- Hejazi, S. R. and Saghafian, S. (2005). Flowshop-scheduling problems with makespan criterion: a review. *International Journal of production Research*, 43(14): 2895-2929.
- Hendtlash, T. (2001). *A Combined Swarm differential evolution algorithm for optimization problems*. Fourteenth international conference on industrial and engineering applications of artificial intelligence and expert systems, Lecture notes in computer Science, Springer Verlag, 2070: 11 – 18.

- Heppner, F. and Grenander, U. (1990). *A stochastic Nonlinear Model for Coordinated Bird Flocks*. In S. Krasner, editor, *The Ubiquity of Chaos*, AAAS Publications.
- Hick, W. E. (1952). On the rate of gain of information. *Journal of experimental Psychology*. 45:188-196
- Hiroki, S. (2008). Collective Dynamics of Complex Systems Research Group. *Department of Bioengineering Binghamton University, State University of New York, 8th Understanding Complex Systems Conference 2008*.
- Ho, S. L. Shiyou, Y. Guangzheng, N. Lo, E. W.C. and Wong, H.C. (2005). A particle swarm optimization based method for multiobjective design optimizations. *IEEE Transactions on Magnetics*, 41(5): 1756–1759, May 2005.
- Holland, J. (1962). Outline for a Logical Theory of Adaptive Systems. *Journal of the ACM*, 3: 297-314.
- Homem de Mello, L. S. and Sanderson (1990). A. C. AND/OR graph representation of assembly plans. *IEEE Transactions on Robotics and Automation*. 6(2): 188-199.
- Homem de Mello, L. S. and Sanderson, A. C. (1991). A correct and complete algorithm for the generation of mechanical assembly sequences. *IEEE Transactions on Robotics and Automation*. 7(2): 228-240.
- Homen de Mello, L. S. and Sanderson, A. C. (1991). Representation of mechanical assembly sequences. *IEEE Transactions on Robotics and Automation*. 7(2): 211-227.
- Hong, D. S. and Cho, H. S. (1997). Generation of robotic assembly sequences with consideration of line balancing using simulated annealing. *Robotica*. 15: 663–673.
- Hong, D. S. Cho, H. S. (1999). A genetic-algorithm-based approach to the generation of robotic assembly sequences. *Control Eng Pract* 7: 151–159.
- HongGuang, L. and Cong, L. (2010). An assembly sequence planning approach with a discrete particle swarm optimization algorithm. *Int J Adv Manuf Technol*. 170(010): 2519-4.
- Hooke, R. and Jeeves, T.A. (1961). "Direct Search" solution for numerical and statistical problems. *Journal of the Association for Computing Machinery (ACM)*, 1961, (8): 212-229.

- Hu, X. Eberhart, R. C. and Shi, Y. (2003). Particles swarm with extended memory for multiobjective optimization. *In Proceedings of the 2003 IEEE Swarm Intelligence Symposium*, 193–197, Indianapolis, Indiana, USA, April 2003. IEEE Service Center.
- Hu, X. Shi, Y. Eberhart, R. (2004). Recent advances in particle swarm. *Proceedings of the IEEE Congress on Evolutionary Symposium (CEC 2004)*.
- Hui, C. Yuan, L. Kai-Fu, Z. (2009). Efficient method of assembly sequence planning based on GAAA and optimizing by assembly path feedää for complex product. *Int J Adv Manuf Technol* 42(11–12): 1187–1204.
- Hyman, R. (1953). Stimulus information as a determinant of reaction time. *Journal of Experimental Psychology*. 45: 188-196.
- Jiapeng, Y. Chengen, W. Jianxi, W. (2012). Assembly sequence planning based on max-min ant colony system. *Journal of Mechanical Engineering*, 48(23): 152-166.
- Jiapeng, Y. Yufei, X. Chengen, W. (2011). Method for determination of geometric dismountability based on extended interference matrix. *Journal of Mechanical Engineering*. 47(21) : 146-156.
- Jiapeng, Y. Chengen, W. Wenlei, Z. (2010a). Method for automatic generation of exploded view based on assembly sequence planning. *Journal of Mechanical Engineering*, 46(21): 149-157.
- Jiapeng, Y. Chengen, W. Wenlei, Z. (2010b). Automatic acquiring method for assembly relation matrix of complex product. *Computer Integrated Manufacturing Systems*, 16(2): 249-255.
- Jiapeng, Y. Chengen, W. Wenlei, Z. *et al.*, (2009). Assembly sequence planning based on priority rules screening. *Journal of Northeastern University*. 30(11): 1636-1640.
- Jing, Z. Jie, S. and Qiwei, H. (2010). An Approach to Assembly Sequence Planning using Ant Colony Optimization. *International Conference on Intelligent Control and Information Processing*, August 13-15, 2010 - Dalian, China.
- Kemal, A. Orhan, E. Alper, D. (2007). Using ant cologny optimization to solve hybrid flowshop scheduling problems. *Int J Adv Manuf Technol*, 35:541-550

- Kennedy, J. and Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings of the 1995 IEEE International Conference on Neural Networks*. 1942-1948, IEEE Press.
- Kennedy, J. and Eberhart, R. C. (1997). A Discrete Binary Version of the Particle Swarm Algorithm. *Proc. of the conference on Systems, Man, and Cybernetics SMC97*, 5: 4104-4109.
- Kennedy, J. Eberhart, R. C. and Shi, Y. (2001). *Swarm Intelligence*. Morgan Kaufmann.
- Kim, Y. K., Hyun, C. J. and Kim, Y. (1996). Sequencing in mixed-model assembly lines: A genetic algorithm approach, *Computers & Operations Research* 23: 1131–1145.
- Koza, J. (1992). *Genetic Programming: On the Programming of Computers by means of Natural Selection*. Massachusetts: MIT Press, Cambridge.
- Lampinen, J. (2001). *A bibliography of differential evolution algorithm*. Lappeenranta University of Technology, Department of Information Technology, Laboratory of Information Processing, *Technical Report*.
- Lampinen, J. Zelinka, I. (1999). Mixed Integer-Discrete-Continuous Optimization By Differential Evolution, Part 1: the optimization method. In: Ošmera, Pavel (ed.) (1999). *Proceedings of MENDEL'99, 5th International Mendel Conference on Soft Computing*. Brno University of Technology, Brno (Czech Republic), 71–76. ISBN 80-214-1131-7.
- Laperriere, L. El-Maraghy, H. A. (1996). GAPP: A genetic assembly process planner. *J Manuf Syst* 15(4): 282–293.
- Laperriere, L. El-Maraghy, H. A. (1994). Assembly sequence planning for simultaneous engineering. *International Journal for Advance Manufacturing Technology*. 9: 231-244.
- Lazzerini, B. Marcelloni, F. (2000). A genetic algorithm for generating optimal assembly plans. *Artif Intell Eng* 14: 319–329.
- Lee, S. and Ko, K. (1987). Automatic assembling procedure generation from mating conditions. *Computer Aided Design*. 19(1), 3-10.
- Lee, S. and Shin, Y. G. (1988). Automatic construction of assembly partial order graphs. *International Conference on Computer Integrated Manufacturing*. Rensselaer Polytechnic Institute. 23-25 May, 383-392.

- Lei, Z. Yuan, L. Jianfeng, Y. (2011). Assembly Sequence Concomitant Planning Method Based for the Variation of Constraint. *Journal of Mechanical Engineering*, 47(5): 149-155.
- Leu, Y., Matheson, L. A. and Rees, L. P. (1996). Sequencing mixed-model assembly lines with genetic algorithms, *Computers and Industrial Engineering* 30: 1027–1036.
- Li, H. Guo, S. Li, C. Sun, J. (2013). A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm. *Knowledge-Based Systems*, 37: 378-387.
- Li, J. R. Khoo, L. P. Tor, S. B. (2003). A tabu-enhanced genetic algorithm approach for assembly process planning. *J Intell Manuf* 14: 197–208.
- Li, M. Bo Wu, Youmin Hu, Chao Jin and Tielin Shi (2013). A hybrid assembly sequence planning approach based on discrete particle swarm optimization and evolutionary direction operation. *Int J Adv Manuf Technol*, DOI 10.1007/s00170-013-4782-7
- Li, S. X. Shan, H. B. (2008). GSSA and ACO for assembly sequence planning: a comparative study. *In: Proceedings of the IEEE international conference on automation and logistics, ICAL 2008*, 1270–1275.
- Lin, A. C. and Chang, T. C. (1991). Automated assembly planning for 3-dimensional mechanical products. *Proceeding of the 1991 NSF Designand Manufacturing System Conference*. NSF, 523-531.
- Lin, S. M. (2013). Analysis of service satisfaction in web auction logistics service using a combination of fruit fly optimization algorithm and general regression neural network. *Neural Computing & Applications*, 22(3-4): 783-791.
- Liu, B. Wang, L. Jin, Y. H. (2007). An effective PSO-based memetic algorithm for flow shop scheduling. *IEEE Trans Syst Man Cybern Part B Cybern* 37(1): 18–27.
- Løvberg, M. and Krink, T. (2002). Extending Particle Swarm Optimizers with Self-Organized Criticality. *In Proceedings of the Fourth Congress on Evolutionary Computation*. 2: 1588-1593.
- Lu, C., Wong, Y.S., Fuh, J.Y.H. (2006). An enhanced assembly planning approach using a multi-objective genetic algorithm. *Proc Inst Mech Eng Part B, J Eng Manuf*. 220(2): 255–272.

- Lv, H. G. Lu, C. Zha, J. (2010). A hybrid DPSO-SA approach to assembly sequence planning. *In: IEEE international conference on mechatronics and automation, ICMA 2010*, 5589203, 1998–2003.
- Lv, H. Lu, C. (2010). An assembly sequence planning approach with a discrete particle swarm optimization algorithm. *Int J Adv Manuf Technol* 50(5–8): 761-770.
- Mansouri, S. A. (2005). A multi-objective genetic algorithm for mixed-model sequencing on jit assembly lines, *European Journal of Operational Research* 167: 696–716.
- Marian, R. M. Luong, H. S. and Abhari, K. (2006). A genetic algorithm for the optimization of assembly sequence. *Comput Ind Eng.* 50: 503– 527.
- Maurice C. (2006). *Particle Swarm Optimization*. (ISTE) Kindle Edition.
- McMullen, P. R. (2010). Jit mixed-model sequencing with batching and setup considerations via search heuristics, *International Journal of Production Research* 48: 6559–6582.
- Michalewicz, Z. (1996). *Genetic Algorithms + Data Structures = Evolution Programs*. Third edition. Berlin: Springer-Verlag.
- Michalewicz, Z. and Fogel, D. (2000). *How to Solve It: Modern Heuristics*. Berlin: Springer-Verlag.
- Milner, J. M. Graves, S. C. Whitney, D. E. (1994). Using simulated annealing to select least-cost assembly sequences. *Proceedings of IEEE International Conference on Robotics and Automation*. 2058–2063
- Mohan, C. and Al-Kazemi, B. (2001). Discrete Particle Swarm Optimization. *In Proceedings Workshop on Particle Swarm Optimization*. Purdue School of Engineering and Technology, USA.
- Mohd Fadzil, F. R. Hutabarat, W. Tiwari, A. (2012). A review on assembly sequence planning and assembly line balancing optimization using soft computing approaches. *Int J Adv Manuf technol*, 59: 335-349.
- Moon, D. S. Park, B. Y. (2007). Genetic algorithms for concurrent assembly planning. *In: Regional computational conference*, 214–219.
- Moore, J. and Chapman, R. (1999). *Application of particle swarm to multiobjective optimization*. Department of Computer Science and Software Engineering, Auburn University.

- Motavalli, S. Islam, A. (1997). Multi-criteria assembly sequencing. *Comput Ind Eng.* 32(4): 743–751.
- Murty, K. G. (1992). *Network programming*. Chapter 7, 405-435. Englewood Cliff. N. J. Printice Hall.
- Omran, Mohd. G.H. Engelbrecht, A. P. Salman, Ayed (2007). Differential Evolution based Particle Swarm Optimization. *IEEE Swarm Intelligence Symposium (SIS 2007)*, 112 – 119.
- Onwubolu, G. Davendra, D. (2006). Scheduling flow shops using Differential evolution algorithm. *European Journal of Operational Research*, 171: 674-692.
- Pan, C. Smith, S. Smith, G. (2006). Automatic assembly sequence planning from STEP CAD files. *Int J Comput Integr Manuf* 19(8): 775–783.
- Pan, W. T. (2012). A new fruit fly optimization algorithm: taking the financial distress model as an example. *Knowledge-Based Systems*, 26(2): 69–74.
- Pardalos, P. Migdalas, A. and Burkard, R. (2002). *Combinatorial and Global Optimization*. World Scientific Publishing Company.
- Pedersen, M. E. H. and Chipperfield, A. J. (2008). *A. J. Parameter tuning versus adaptation: Proof of principle study on differential evolution*. Hvas Laboratories, 2008. HL0802.
- Pedersen, M. E. H. (2010). *Tuning & Simplifying Heuristical Optimization*. (PhD Thesis). School of Engineering Sciences, University of Southampton, United Kingdom.
- Pedersen, M. E. H. and Chipperfield, A. J. (2008). *Local Unimodal Sampling*. Hvas Laboratories, 2008. HL0801.
- Pedersen, M. E. H. and Chipperfield, A. J. (2010). *Simplifying Particle Swarm Optimization*. *Applied Soft Computing*, 10: 618-628.
- Peng, L. Hong, L. Xiangwei, Z. *et al.*, (2011). Approach for dynamic group automatic aggregation path planning based on improved Firefly Algorithm. *Application Research of Computers*. 28(11): 4146-4149.
- Ponnambalam, S. G. , Aravindan, P. and Subba Rao, M. (2003). Genetic algorithms for sequencing problems in mixed-model assembly lines, *Computers and Industrial Engineering* 45: 669–690.

- Price, K. Storn, R. M. and Lampinen, J. A. (2005). *Differential Evolution: A Practical Approach to Global Optimization*. (Natural Computing Series), 1st Ed. New York: Springer-Verlag.
- Price, K. (1996). Differential Evolution: A Fast and Simple Numerical Optimizer. *Biennial Conference of the North American Fuzzy Information Processing Society*, 524-527.
- Raidl, G. R. (2006). A unified view on hybrid metaheuristics. *Proc 3rd Int. Workshop Hybrid Metaheuristics*, Gran Canaria, Spain, 1–12.
- Rameshkumar, K. Suresh, R. K. and Mohanasundaram, K. M. (2005). Discrete Particle Swarm optimization (DPSO) Algorithm for permutation flowshop scheduling to minimize makespan. *First International Conference on Natural Computation*. ICNC 2005, Changsha, China, 572–581.
- Raquel, C. R. and Naval, Jr. P. C. (2005). An effective use of crowding distance in multiobjective particle swarm optimization. *In Proceedings of the Genetic and Evolutionary Computation Conference (GECCO-2005)*, 257–264, Washington, DC, USA, June 2005. ACM Press.
- Rardin, R. L (1998). *Optimization in Operations Research*. Prentice-Hall International.
- Ratnaweera, A. C. Halgamuge, S. K. and Watson, H. C. (2002). Particle swarm optimizer with Time Varying acceleration Coefficients. *In proceedings of the International Conference on Soft Computing and intelligent Systems*. 240-255.
- Ray, T. and Liew, K. M. (2002). A swarm metaphor for multiobjective design optimization. *Engineering Optimization*, 34(2): 141–153, March 2002.
- Ray, T. Kang, T. and Chye, S. K. (2000) An evolutionary algorithm for constrained optimization. In Darrell Whitley, David Goldberg, Erick Cantu´-Paz, Lee Spector, Ian Parmee, and Hans-Georg Beyer, editors, *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO'2000)*, 771–777, San Francisco, California: Morgan Kaufmann.
- Rekiek, B. De Lit, P. and Delchambre, A. (2000). Designing mixed-product assembly lines. *IEEE transactions on Robotics and Automation*, 16(3): 268-280.
- Reynolds, C. W. (1987). Flocks, herds, and schools: a distributed behavioral model. *Computer graphics*. 21(4): 25-34.

- Salman, A. (1999). *Linkage Crossover Operator for Genetic Algorithms*. PhD Dissertation. School of Syracuse University, USA.
- Sanderson, A. C. Homem de Mello, L. S. Zhang, H. (1990). Assembly sequence Planning. *AI Magazine*, 11: 62-81.
- Sangwook, L. Jusang, L. Shim, D. Moongu, J. (2007). *Binary Particle Swarm Optimization for Black-Scholes Option Pricing*. Knowledge-Based Intelligent Information and Engineering Systems, Lecture Notes in Computer Science 4692: 85-92, Heidelberg, Springer Berlin.
- Scholl, A., Klein, R. and Domschke, W. (1998). Pattern based vocabulary building for effectively sequencing mixed-model assembly lines, *Journal of Heuristics* 4: 359–381.
- Scholl, A. (1999). *Balancing and sequencing of assembly lines*. Heidelberg. New York: Physica-Verlag.
- Scholl, A. Becker, C. (2006). State-of-the-art exact and heuristic solution procedures for simple assembly line balancing. *Eur J Oper Res*. 168: 666–693.
- Sebaaly, M. F. Fujimoto, H. (1996). A genetic planner for assembly automation. *IEEE Conference on Evolutionary Computation* 401– 406.
- Sebaaly, M. F. Fujimoto, H. (1996). *Assembly sequence planning by GA Search: a novel approach*. Japan/USA Symposium on Flexible Automation 2: 1235–1240.
- Senin, N. Groppetti, R. Wallace, D. R. (2000). *Concurrent assembly planning with genetic algorithms*. Robot Comput Integr Manuf 16: 65–72.
- Shan, H. Li, S. Gong, D. Lou, P. (2006). Genetic simulated annealing algorithm-based assembly sequence planning. *In: IET conference publications*, 524: 1573–1579.
- Shan, H. Zhou, S. Sun, Z. (2009). Research on assembly sequence planning based on genetic simulated annealing algorithm and ant colony optimization algorithm. *Assem Autom* 29(3): 249–256.
- Shao, X., Wang, B., Rao, Y., Gao, L. and Xu, C. (2010). Metaheuristic approaches to sequencing mixed-model fabrication /assembly systems with two objectives, *International Journal of Advanced Manufacturing Technology* 48: 1159–1171.

- Shen, B. Yao, M. and Yi, W. S. (2006). Heuristic information based improved fuzzy discrete PSO method for solving TSP. *9th Pacific Rim International Conference on Artificial Intelligence*. Guilin, China, 859–863.
- Shi, Y. and Eberhart, R. (1998). Parameter selection in particle swarm optimization. *In Evolutionary Programming VII: Proceedings of the Seventh annual Conference on Evolutionary Programming*, 591–600, New York, USA: Springer-Verlag.
- Shi, Y. and Eberhart, R. (1998b). A modified particle Swarm optimizer. In proceedings of the IEEE Congress on Evolutionary Computation. 69-73.
- Shi, Y. and Eberhart, R. (1999). Empirical study of particle swarm optimization. *In Congress on Evolutionary Computation (CEC'1999)*, 1945–1950, Piscataway, NJ: IEEE Press.
- Shicai, S. Rong, L. Yili, *et al.* (2010). Assembly sequence planning based on improved ant colony algorithm. *Computer Integrated Manufacturing System*, 16(6): 1189-1194.
- Shpitalni, M. Elber, G. and Lenze, E. (1989). Automatic assembly of three-dimensional structures via connectivity graphs. *Annals of the CIRP*. 38(1): 25-28.
- Shuang, B. Chen, J. P. and Li, Z. B. (2008). Microrobot based micro-assembly sequence planning with hybrid ant colony algorithm. *Int J Adv Manuf Technol*. 38: 1227–1235.
- Smith, (Chen) S. F. Liu, Y. J. (2001). The application of multi-level genetic algorithm in assembly planning. *J Ind Technol* 17(4): 1.
- Smith, G. C. and Smith, S. F. (1998). Assembly planning - a genetic approach. *Proceedings of the 24th ASME Design Automation Conference*.
- Smith, G. C. and Smith, S. F. (2002). An enhanced genetic algorithm for automated assembly planning. *Robot Comput Integr Manuf*. 18: 355–364.
- Smith, S. S. F. (2004). Using multiple genetic operators to reduce premature convergence in genetic assembly planning. *Comput Ind* 54(1): 35–49.
- Spall, J. (2003). *Introduction to Stochastic Search and Optimization*. 1st edition. Wiley-Interscience.
- Srinivasan, D. and Hou, T. Seow. (2003). Particle swarm inspired evolutionary algorithm (PS-EA) for multiobjective optimization problem. *In Congress on*

- Evolutionary Computation (CEC'2003)*, (3): 2292–2297, Canberra, Australia, December 2003. IEEE Press.
- Stacey, A. Jancic, M. and Grundy, I. (2003) Particle Swarm Optimization with mutation. *In Proceedings of the Congress on Evolutionary Computation*, 1425–1430, Canberra, Australia: IEEE Press.
- Storn, R. and Price, K. (1995). *Differential evolution—A simple efficient adaptive scheme for global optimization over continuous spaces*. Technical report, California: International Computer Science Institute, Berkeley.
- Storn, R. and Price, K. (1996). Minimizing the real functions of the ICEC'96 contest by Differential Evolution. *Int. Conf. on Evolutionary Computation*, Nagoya, Japan, 842-844.
- Sun, X. and Sun, L. (2005). *Ant colony optimization algorithms for scheduling the mixed model assembly lines*. ICNC 3, Lecture Notes in Computer Science, 3612: 911-914, Springer.
- Su, Q. (2009). A hierarchical approach on assembly sequence planning and optimal sequence analyzing. *Robot Comput-Integr Manuf* 25(1): 224–234.
- Su, W. and Bo, M. (2006). *Ant colony optimization for manufacturing resource scheduling problem*. In International Federation for Information processing (IFIP), Knowledge Enterprise: Intelligent Strategies In Product design, Manufacturing, and Management, eds. K. Wang, Kovaces G., Wozny M., Fang M., (Boston: Springer), 207: 863-868.
- Suresh, G. Sahu, S. (1994). Stochastic assembly line balancing using simulated annealing. *Int J Prod Res.* 32(8): 1801–1810.
- Talbi, E. G. (2002). *A taxonomy of hybrid metaheuristics*. J. Heur. 8(5): 541–564.
- Talibi, H. and Bautouche (2004). Hybrid Particle Swarm with Differential Evolution for Multimodal Image Regression”, *IEEE International Conference on Industrial Technology*, 3:1567-1573.
- Tamer, M. K. Husam, K. M. Y. Abdel Aziz, (2006). A Binary Particle Swarm Optimization for Optimal Placement and Sizing of Capacitor Banks in Radial Distribution Feeders with Distorted Substation Voltages. *AIML'06 international conference*, 13-15, Sharm Al-Sheikh, Egypt.
- Tchomté, S. K. Gourgand, M. Quilliot, A. (2007). Solving resources-constrained project scheduling problem with particle swarm optimization. *Multidisciplinary Int'l Scheduling Conference (MISTA'2007)*, 251-258.

- Tony, W. (2005). *Expert Assessment of Stigmergy*. A Report for the Department of National Defence 16 May 2005, School of Computer Science Room 5302 Herzberg Building Carleton University.
- Tseng, H. Chen, M. Chang, C. Wang, W. (2008). Hybrid evolutionary multi-objective algorithms for integrating assembly sequence planning and assembly line balancing. *Int J Prod Res* 46(21): 5951–5977.
- Tseng, H. Li, J. and Chang, Y. (2004). Connector-based approach to assembly planning using a genetic algorithm. *Int J Prod Res*. 42(11): 2243–2261.
- Tseng, H. Tang, C. (2006). A sequential consideration for assembly sequence planning and assembly line balancing using the connector concept. *Int J Prod Res* 44(1): 97–116.
- Tseng, H. E. Wang, W. P. Shih, H. Y. (2007). Using memetic algorithms with guided local search to solve assembly sequence planning. *Expert Syst Appl* 33(2): 451–467.
- Tseng, Y. Chen, J. Huang, F. (2010). A multi-plant assembly sequence planning model with integrated assembly sequence planning and plant assignment using GA. *Int J Adv Manuf Technol* 48(1–4): 333–345.
- Tseng, Y. Yu, F. Huang, F. (2011). A green assembly sequence planning model with a closed-loop assembly and disassembly sequence planning using a particle swarm optimization method. *International Journal of Advanced Manufacturing Technology*. 57(9-12) : 1183-1197.
- Udeshi, T. Tsui, K. (2005). Assembly sequence planning for automated micro assembly. In: *IEEE International symposium on assembly and task planning*, 2005: 98–105.
- Uzsoy, R. (1991). Production scheduling algorithms for a semiconductor test facility. *IEEE Transactions on semiconductor manufacturing*. 4(4): 270-279.
- Van den Bergh, F. (2002). *An analysis of particle swarms optimizers*. Department of Computer Science. University of Pretoria, South Africa.
- Van Laarhoven, P. and Aarts, E. (1987). *Simulated Annealing: Theory and Applications*. Kluwer Academic Publishers.
- Venter, G. and Sobieszczanski-Sobieski, J. (2002). Particle Swarm Optimization. In *the 43rd AIAA/ASME/ASCE/AHA/ASC Structures, Structural Dynamics and Materials Conference*. Denver, Colorado, USA.

- Voß, S. (2006). Hybridizing metaheuristics: The road to success in problem solving. *6th Eur. Conf. Evol. Comput. Combinat. Optim.* (Slides of an invited talk at the EvoCOP 2006), Budapest, Hungary.
- Waarts, J. J., Boneschanscher, N. and Bronsvort, W. F. (1992). A semi-automatic assembly sequence planner. *Proceedings of the 1992 IEEE International Conference on Robotics and Automation*. Nice, France, 2431–2438.
- Wang, J. F. Liu, J. H. and Zhong, Y. F. (2005). A novel ant colony algorithm for assembly sequence planning. *Int J Adv Manuf Technol*. 25: 1137–1143.
- Wang, L. Shadi, K. Hsi-Yung, F. and Buchal, R. O. (2009). Assembly process planning and its future in collaborative manufacturing: a review. *Int J Adv Manuf Technol*. 41:132–144.
- Wang, M. Ye, B. L. (2008). Assembly planning based on a particle swarm optimization algorithm. *Dual Use Technol Prod* 1:44–45.
- Wang, W. P. Tseng, H. E. (2009). Complexity estimation for genetic assembly sequence planning. *J Chin Inst Ind Eng* 26(1): 44–52.
- Wang, Y. Liu, J. H. (2010). Chaotic particle swarm optimization for assembly sequence planning. *Robot Comput Integr Manuf* 26(2): 212–222.
- Wang, B. (2010). Sequencing mixed-model production systems by modified multi-objective genetic algorithms. *Chinese Journal of Mechanical Engineering (English Edition)* 23: 537–546.
- Whitney, D. E. (2004). Mechanical assemblies: Their Design, Manufacture, and Role in Product Development, Chapter 7, 180-210. Oxford University Press.
- Wolter, J. D. (1990). On the automatic generation of assembly plans. *Proceedings of the IEEE International Conference on Robotics and Automation*. (1): 62-68.
- Xing, Y. Wang, Y. Zhao, X. (2010). A particle swarm algorithm for assembly sequence planning. *Adv Mat Res* 3243: 97–101.
- Xin, B. Chen, J. Zhang, J. Fang, H. and Peng, Z. (2011). Hybridizing Differential Evolution and Particle Swarm Optimization to Design Powerful Optimizers: A Review and Taxonomy, *IEEE Transactions on Systems, Man, and Cybernetics* part C: Applications and reviews.
- Xu, J. Q. Liang, B. Wang, J. S. Xu, X. D. and Zhang, B. P. (1994). An approach to automatic assembly sequences generation. *Proceedings of 2nd Asian Conference on Robotics and its Application*. 612-615.

- Yang, X. S. (2009). Firefly algorithms for multimodal optimization. *Proc. of the 5th International Conference on Stochastic Algorithms : Foundations and Applications*. Berlin: Springer-Verlag, 2009: 169-178.
- Yang, X. S. (2010a). Firefly algorithm, stochastic test functions and design optimization. *Int. J. Bio-Inspired Computation*. London: Springer, 2010: 78-84.
- Yang, X. S. (2010b). Firefly algorithm, L'evy flights and global optimization. *Research and Development in Intelligent Systems XXVI*. London : Springer, 2010: 209-218.
- Yoshida, H. Kawata, K. Fukuyama, Y. and Nakanishi, Y. (1999). A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Stability. *In Proceedings of the International Conference on Intelligent System Application to Power Systems*. Rio de Janeiro, Brazil, 117–121.
- Yu, H. Yu, J. Zhang, W. (2009). A particle swarm optimization approach for assembly sequence planning. *7th International Conference on E-Engineering and Digital Enterprise Technology*. Shenyang, China. Clausthal-Zellerfeld , Germany : Trans. Tech. Publications, 2009 : 1228-1232.
- Zha, X. F. Samuel, Lim, Y. E. and Fok, S. C. (1998). Integrated Knowledge-Based Assembly Sequence Planning. *Int J Adv Manuf Technol* (1998) 14:50-64.
- Zha, X. F. Lim, S. Y. E. Fok, S. C. (1999). Development of Expert System for Concurrent Product Design and Planning for Assembly. *Int J Adv Manuf Technol* (1999) 15: 153-162, Springer-Verlag.
- Zhan, Z. H. Zhang, J. (2009). *Discrete Particle Swarm Optimization for Multiple Destination Routing Problems*. Applications of Evolutionary Computing, EvoWorkshops 2009: EvoCOMNET, EvoENVIRONMENT, EvoFIN, EvoGAMES, EvoHOT, EvoIASP, EvoINTERACTION, EvoMUSART, EvoNUM, EvoSTOC, EvoTRANSLOG, Tubingen, Germany, 117–122.
- Zhang, J. Sun, J. He, Q. (2010). An approach to assembly sequence planning using ant colony optimization. *In: Proceedings of 2010 international conference on intelligent control and information processing, ICICIP 2010, 2: 230–233*.
- Zhang, L.-P Yu, H.-J. and Hu, S.-X. (2005). Optimal choice of parameters for particle Swarm Optimization. *Journal of Zhejiang Univ. SCI*. 528-534. 6A(6).

- Zhang, W. (1989). Representation of assembly and automatic robot planning by Petri net. *IEEE Transactions on Systems, Man and cybernetics*. 29(2): 418-422.
- Zhang, W-T. and Xie, X-F. (2003). DEPSO: hybrid Particle Swarm with Differential Evolution Operator. *IEEE International Conference on Systems Man and Cybernetics*, (4): 3816 – 3821.
- Zheng, Y-L. Long-Hua, M. Li-Yan, Z. and Ji-Xin, Q. (2003). On the convergence analysis and parameter selection in particle swarm optimization. *In Proceedings of the Second International Conference on Machine Learning and Cybernetics*, 1802–1807. IEEE Press.
- Zheng, B. Li, M. Zhang, Y. Ma, J. (2013). Research on assembly sequence planning based on firefly algorithm. School of Mechanical Engineering. Xiangtan University. Xiangtan. DOI 10.3901/JME.2013.11.177
- Zhou, W. Zheng, J. Yan, J. Wang, J. (2010). A novel hybrid algorithm for assembly sequence planning combining bacterial chemotaxis with genetic algorithm. *Int J Adv Manuf Technol* 52(5–8): 715–724.
- Zhu, X. Hu, S. J. Koren, Y. and Marin, S. P. (2006). Modeling of manufacturing complexity in mixed-model assembly lines. *In proceedings of 2006 ASME International Conference on Manufacturing Science and Engineering*, Ypsilanti. MI. USA.