

ASSEMBLY SEQUENCE PLANNING USING HYBRID
BINARY PARTICLE SWARM OPTIMIZATION

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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.

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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.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	xii
	LIST OF FIGURES	xvi
	LIST OF ABBREVIATION	xxi
	LIST OF SYMBOLS	xxiii
	LIST OF APPENDICES	xxvi
1	INTRODUCTION	1
	1.1 Background	1
	1.2 Problem statement	2
	1.3 Research objectives	4
	1.4 Research methodology	5
	1.5 Research scope and limitation	6
	1.6 Thesis organization	6
2	LITERATURE REVIEW	8
	2.1 Assembly sequence planning (ASP)	8
	2.1.1 Introduction	8

2.2	Optimization methods	16
2.3	Optimization algorithms	17
2.4	Evolutionary algorithms	18
2.4.1	Simulated annealing optimization.	19
2.4.2	Genetic algorithms optimization.	20
2.4.3	Ant colony optimization.	23
2.4.4	Swarm intelligence.	27
2.4.5	Binary Particle swarm optimization (BPSO).	28
2.4.5.1	History of PSO	28
2.4.5.2	Swarms collective behavior	31
2.4.5.3	Neighbourhoods topologies	32
2.4.6	Discrete particle swarm optimization.	37
2.5	Differential Evolution	38
2.6	Summary	39
3	METHODOLOGY	41
3.1	Introduction.	41
3.2	Time minimization for assembly sequence planning	42
3.3	Optimization	43
3.3.1	Gradient-Based Optimization	44
3.3.2	Heuristic Optimization	44
3.3.3	Constraints	45
3.3.4	Penalty Functions	45
3.3.5	General Constraints	46
3.3.6	Phases of Constrained Optimization	46
3.3.7	Difficulty of Constrained Optimization	47
3.3.8	Meta-Optimization	47
3.3.9	Fitness Normalization	49
3.4	Optimization Methods	49
3.4.1	Gradient Descent (GD)	50
3.4.2	Pattern Search (PS)	51
3.4.3	Local Unimodal Sampling (LUS)	52
3.5	Formulation and Analysis of the ASP Mathematical	

Models	53
3.5.1 Fitness function formulation.	56
3.5.2 Time of assembly optimization.	61
3.5.3 Number of Tool Changing and the Combined Objective Function	65
3.6 Assembly sequence planning approach with PSO.	67
3.6.1 Concepts of PSO algorithm.	67
3.6.1.1 Mathematical illustration for PSO algorithm.	69
3.6.1.2 Example calculation using PSO algorithm.	72
3.6.2 Aspects of PSO algorithm.	75
3.7 Differential Evolution.	82
3.7.1 Initial Population.	83
3.7.2 Mutation with Difference Vectors.	85
3.7.3 Crossover.	85
3.7.4 Selection.	86
3.8 Methodology to solve single objective and multi-objective problems.	89
3.8.1 Proposal to solve assembly sequence planning.	92
3.8.1.1 Sequence within range setting Algorithm.	93
3.8.1.2 Archive system and precedence constraints matrices interaction.	94
3.8.1.3 Verification of PSO performance.	101
3.8.1.4 Update velocity, position, pbest and gbest.	102
3.8.1.5 Checking feasibility of sequence.	103
3.8.1.6 Sequences Parts-Location Diversity.	104
3.9 Tool changing approach with particle swarm optimization.	105
3.9.1 Formulation of the fitness function for	

	tool changing problem.	105
3.10	Discrete / binary PSO approach to solve ASP.	106
3.10.1	Discrete PSO approach to solve ASP.	106
3.10.2	Binary particle swarm optimization approach to solve ASP.	109
3.11	Summary	112
4	RESULTS AND DISCUSSION	113
4.1	PSO approach to optimize ASP	113
4.1.1	The effects of iterations (300, 800, 1500, 3000, 5000, 8000)	114
4.1.2	The effects of swarm size (10, 20, 30, 40, 50)	121
4.1.3	The Effects of swarm size of PSO algorithm in ASP optimization process	126
4.1.3.1	Swarm size of (100, 200, 300).	126
4.1.3.2	Swarm size of (20, 40, 60, 80, 100)	128
4.1.4	The effects of control parameters of PSO in ASP optimization process.	129
4.1.4.1	The effects of weight of inertia ($w= 1.0, 0.8, \text{ and } 0.5$).	130
4.1.4.2	The effects of weight of inertia ($w= 0.9, 0.5, 0.1$).	131
4.1.4.3	The effect of change of cognitive coefficient ($c_1=0.9, 0.5, 0.1$).	132
4.1.4.4	The effect of change of social coefficient ($c_2=0.9, 0.5, 0.1$).	133
4.2	Binary PSO approach to optimize assembly sequence planning	134
4.2.1	The effects of swarm size (40, 50, 60)	134
4.2.2	The effects of swarm size (20, 60 / iteration 2000)	137
4.2.3	The effects of swarm size (50 particles / iteration 8000)	138

4.3	PSO and Binary PSO approach to minimize the number of tool changing.	149
4.3.1	The effects of swarm size (20, 60, 100) in PSO optimizing tool changing	149
4.3.2	The effects of swarm size (20, 60, 100) in Binary PSO to optimize tool change	150
4.3.3	The effect of weight of inertia (0.3, 0.6, 0.9) in PSO to optimize tool change.	152
4.3.4	The effect of weight of inertia (0.3, 0.6, 0.9) in BPSO to optimize tool change	153
4.3.5	The effect of cognitive coefficient ($c_1 = 0.6, 1.0, 1.4$) in PSO to optimize tool change	154
4.3.6	The effect of cognitive coefficient ($c_1 = 0.6, 1.0, 1.4$) in BPSO to optimize tool change	155
4.3.7	The effect of social coefficient ($c_2 = 0.6, 1.0, 1.4$) in classic PSO to optimize tool change	156
4.3.8	The effect of social coefficient ($c_2 = 0.6, 1.0, 1.4$) in binary PSO to optimize tool change	157
4.3.9	The Performance Comparison Between PSO and Binary PSO in Optimizing Number of Tool Changing	158
5	CONCLUSION AND FUTURE WORK	160
5.1	Conclusion	160
5.2	Future work	164
	REFERENCES	166
	APPENDICES A-C	188-277

LIST OF TABLES

TABLE NO.	TITLE	PAGE
2.1	Summary of ASP research using soft computing (2002-2010)	40
3.1	Precedence constraints between part (i) and part (j)	54
3.2	General format of Factory Capacity Table (FCT)	55
3.3	Transfer complexity values between any two values of a ten parts assembly	59
3.4	Assembly Precedence Matrix (PM) of the 19 components product	63
3.5	Coefficient of various assembly items	64
3.6	Tool types and total number of tool changes	105
3.7	Tool types changed with different parts	106
4.1	Averaged <i>gbest</i> values for number of iterations 300, 800, 1500	115
4.2	Diversity improvement with weight incorporation to sequences when runs in BPSO with iterations 300, 800, and 1500	116
4.3	Averaged <i>gbest</i> values for number of iterations 3000, 5000, and 8000	118
4.4	Diversity improvement with weight incorporation to sequence's when runs in BPSO with iterations 3000, 5000, and 8000	118
4.5	BPSO to obtain averaged <i>gbest</i> values, with varied iterations and 10 particles	120

4.6	Averaged <i>gbest</i> values for number of particles 10, 20, & 30	122
4.7	Diversity improvement with weight incorporation to sequence's when runs in BPSO with Particles 10, 20, 30, 40 and 50 with constant iteration of 800	122
4.8	Averaged <i>gbest</i> values for number of particles 40, and 50	123
4.9	Number of particles with averaged <i>gbest</i> values	124
4.10	Comparison of results obtained by PSO with SA and GA algorithms	125
4.11	PSO Average Gbest Value in different swarm size	127
4.12	PSO algorithm mean fitness value with different swarm size effect	128
4.13	Optimal Fitness (Gbest) Value of PSO Algorithm	129
4.14	Optimal fitness (Gbest) value of PSO for 30 particles, 100 iterations.	130
4.15	Optimal fitness (Gbest) value of PSO for 100 particles, 500 iterations.	131
4.16	Optimal (Gbest) value of PSO with varied cognitive coefficient (c_1)	132
4.17	Optimal fitness (Gbest) value of PSO with varied Social coefficient c_2	133
4.18	Results of Binary PSO with 40 Particles 500 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42	135
4.19	Results of Binary PSO with 50 Particles 500 iterations, inertia weight (0.6), cognitive coefficient (c_1), and social coefficient (c_2) are =1.42	135
4.20	Results of Binary PSO with 60 Particles 500 iterations, inertia weight (0.6), cognitive coefficient (c_1) and social coefficient (c_2) are =1.42.	136
4.21	Results of Binary PSO with pop = 40, 50, 60 particles and 500 iterations.	136
4.22	Results of Binary PSO with 20 Particles 2000 iterations.	137

4.23	Results of BPSO with 60 Particles and 2000 iterations	137
4.24	Results of BPSO with 50 Particles and 8000 iterations	138
4.25	Verification by comparison of results obtained using Simulating Annealing (SA), Genetic Algorithm (GA), with that obtained using PSO, and Binary PSO with 500 iterations.	139
4.26	Obtained results of gbest and average gbest for PSO, BPSO, and BPSODE	141
4.27	Eight test functions implemented in the comparative study of PSO, BPSO, and BPSODE algorithms	142
4.28	Comparative results for eight benchmark problems	147
4.29	Performance Evaluation Criteria (<i>Performance measure</i>)	148
4.30	Results of PSO with pop = 20, 60, 100 particles and 200 iterations.	150
4.31	Results of Binary PSO with swarm size of 20, 60, 100 particles and 200 iterations.	151
4.32	Optimal fitness (Gbest) value of PSO algorithm for 100 particles, 200 iterations, cognitive coefficient (c_1) = social coefficient $c_2 = 1.4$	153
4.33	Optimal fitness (Gbest) value of Binary PSO algorithm for 100 particles, 200 iterations, cognitive coefficient (c_1) = social coefficient $c_2 = 1.4$	154
4.34	Mean fitness (Gbest) value of PSO algorithm for 100 particles, 200 iterations, social coefficient $c_2 = 1.4$ with variable cognitive coefficient (c_1).	155
4.35	Mean fitness (Gbest) value of Binary PSO algorithm for 100 particles, 200 iterations, social coefficient $c_2 = 1.4$ with variable cognitive coefficient (c_1).	156
4.36	Mean fitness (Gbest) value of PSO algorithm for 100 particles, 200 iterations, cognitive coefficient (c_1)=1.4 with variable social coefficient (c_2).	157
4.37	Mean fitness (Gbest) value of Binary PSO algorithm for 100 particles, 200 iterations, cognitive coefficient (c_1)=1.4	

with variable social coefficient (c_2).

158

LIST OF FIGURES

FIGURE No.	TITLE	PAGE
1.1	An assembly product, which consist of 13 components	2
2.1	Assembled parts of example assembly from Industry (AFI)	11
2.2	Liaison Diagram for the example Assembly from Industry (AFI)	11
2.3	Example of feasible sequences for the Assembly from Industry (AFI) product, which consists of 11 parts	12
2.4	Simple product	13
2.5	Relations between components	13
2.6	Example of feasible sequences for a simple product consist of 4 parts	13
2.7	Assembly process planning	15
2.8	Popular optimization methods for ASP	25
2.9	Optimization methods used for assembly layout and line balancing	26
2.10	The separation rule	28
2.11	The alignment rule	29
2.12	The cohesion rule	29
2.13	Location of roost attract agent.	30
2.14	Agent memorized closest location to the roost.	30
2.15	Location information shared with its neighbors.	31
2.16	Collective behaviors	31
2.17	Geographical neighborhood	32
2.18	Ring (local best) type of Social Network Structures	33
2.19	Star (Global best) type of Social Network Structures	34

2.20	Advanced Social Network Structures examples (a) Wheel, (b) Cluster, (c) Von Neumann, and (d) Pyramid	34
3.1	Assembly precedence diagram of 8 parts	54
3.2	Precedence diagram of a 19 components product	63
3.3	The research workflow	66
3.4	Illustration of PSO original equation with c_1 and c_2 are '0'.	69
3.5	Illustration of PSO original equation with parameter $c_2 = 0$	70
3.6	Illustration of PSO original equation with parameter $c_1 = 0$	70
3.7	Illustration of PSO original equation with parameter c_1 & $c_2 \neq 0$	71
3.8	Initialize swarm	72
3.9	Apply new velocity	73
3.10	Up date velocities	74
3.11	The flow chart of the original or Classic PSO	80
3.12	Programming flow chart	81
3.13	Differential evolution works directly with the floating-point valued variables of the objective function not with their (binary) encoding.	87
3.14	Illustrating a simple DE mutation scheme in 2-D parametric space	88
3.15	Different possible trial vector formed due to uniform/binomial crossover between the target and the mutant vectors in 2-D search space	88
3.16	The proposed flow chart of the methodology to solve single and Multi-Objective problems.	91
3.17	Flow chart of the detailed proposal algorithm	92
3.18	Value of 10 changed to 4	93
3.19	Precedence constraints diagram of 6 components example	95
3.20	Free to assemble comonents stored in archive 1	95
3.21	Component from archive 1 stored in archive 2	95
3.22	Remaining free to assemble components in archive 1	95
3.23	Updating archive 2 with the next parts to load	95
3.24	Precedence Matrices with 'update-1' interaction	96
3.25	Archive 1 stored components of output '1' due matrices	

	interaction	96
3.26	Archive 2 stored components 5, 2, and 3	96
3.27	Precedence Matrices with ‘update-2’ interaction	97
3.28	Nonfree-to-assemble component 4 loaded to archive 1	97
3.29	Archive 2 updated and stored components 5, 2, 3, and 4	97
3.30	Precedence Matrices with update-3 interaction	97
3.31	Nonfree-to-assemble component 6 loaded to archive 1	98
3.32	Archive 2 updated and stored components 5, 2, 3, 4 and 6	98
3.33	Precedence Matrices with update-4 interaction	98
3.34	No additional component to be added to archive 1	98
3.35	Archive 2 updated and stored components 5, 2, 3, 4 6 and 1	98
3.36	Mutation process to form a feasible sequence	100
3.37	Example of total assembly time calculation	101
3.38	Check feasibility of sequence	103
3.39	The pseudo-code of Binary PSO algorithm	112
3.40	Conversion of assembly sequence or number of tool changes from decimal value to binary value	113
3.41	Conversion of assembly sequence or number of tool changes from decimal to binary value and then back to decimal value.	113
4.1a	Diversity improvement-non-free parts (300 iterations)	119
4.1b	Diversity improvement-non-free parts (800 iterations)	119
4.1c	Diversity improvement-non-free parts (1500 iterations)	119
4.2a	Diversity improvement-non-free parts (3000 iterations)	121
4.2b	Diversity improvement-non-free parts (5000 iterations)	121
4.2c	Diversity improvement-non-free parts (8000 iterations)	121
4.3	Averaged <i>g_{best}</i> vs number of iterations graph Appendix [C-s. code (a)]	122
4.4	Averaged <i>g_{best}</i> vs number of particles Appendix [C-source code (c)]	126
4.5	PSO Performance with different swarm size in 20 Runs	129
4.6	PSO performance with different swarm size in 20 Runs	131
4.7	PSO performance with different inertia weight (1, 0.8, 0.5).	132
4.8	PSO performance with different inertia weight (0.9, 0.5, 0.1)	133

4.9	PSO performance with varied cognitive coefficient (c_1)	134
4.10	PSO algorithm performance with weight of inertia =0.5, cognitive coefficient $c_1 = 1.0$, while social coefficient c_2 is varied, for 20 runs.	135
4.11	BPSO Min Assembly Time 514.10000 with 50 particle and 8000 iterations, inertia weight 0.6, c_1 and c_2 are 1.42. [Refer to Table 4.21/ Run (1)], Appendix [C-source code (c)]	140
4.12	Fitness value vs. iterations with 10 particles [refer to Table 4.23], Appendix [C-source code (d)]	143
4.13	Performance curve of De Jong's Function 1 (Sphere model) for Binary PSO and Binary PSODE	145
4.14	Performance curves of De Jong's Function 2 (Rosenbrock's valley) Binary PSO and Binary PSODE	145
4.15	Performance curve of Griewangk's function for Binary PSO and Binary PSODE	146
4.16	Performance curve of Schwefel's function for Binary PSO and Binary PSODE	146
4.17	Performance curve of Easom's function for Binary PSO and Binary PSODE	147
4.18	Performance curve of Michalewicz's function for Binary PSO and Binary PSODE	147
4.19	Performance curve of Zakharov's function for Binary PSO and Binary PSODE	148
4.20	Performance curve of Shubert's function for Binary PSO and Binary PSODE	148
4.21	PSO performance with weight of inertia (w) =0.6, cognitive coefficient (c_1)= social coefficient (c_2) =1.4. Appendix [C-source code (b)]	152
4.22	Binary PSO performance with weight of inertia (w) =0.6, cognitive coefficient (c_1)= social coefficient (c_2)=1.4. Appendix (C)-source code-(b)	153
4.23	PSO performance with different weight of inertia while cognitive coefficient c_1 =social coefficient c_2 =1.4. Appendix	

	(C)-source code-(b)	154
4.24	Binary PSO performance with different weight of inertia while cognitive coefficient c_1 =social coefficient $c_2 =1.4$. Appendix (C)-source code-(b)	155
4.25	PSO performance with weight of inertia $w=0.6$, social coefficient $c_2 =1.4$, while different cognitive coefficient c_1 Appendix (C)-source code-(b)	156
4.26	Binary PSO performance with weight of inertia $w=0.6$, social coefficient $c_2 =1.4$, with variable cognitive coefficient c_1 .	157
4.27	PSO performance with weight of inertia $w=0.6$, cognitive coefficient $c_1 =1.4$, with variable social coefficient c_2 value for 20 runs.	158
4.28	Binary PSO performance with weight of inertia $w=0.6$, cognitive coefficient $c_1 =1.4$, with variable social coefficient c_2 value for 20 runs.	159
4.29	PSO performance optimizing number of tool change, with population of 30 particles, and 200 iterations Appendix (C)-source code-(b).	160
4.30	Binary PSO algorithm performance optimizing number of tool changing, with population of 30 particles, and 200 iterations Appendix (C)-source code-(b).	161

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]

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A1	Free parts are fly back to the right behind part 19	222
A2	Average Actual Assembly Time (A_{av}) Calculation (Sequence 1)	224
A3	Average Actual Assembly Time (A_{av}) Calculation (Sequence 2)	225
A4	Average Actual Assembly Time (A_{av}) Calculation (Sequence 3)	226
A5	Average Actual Assembly Time (A_{av}) Calculation (Sequence 4)	227
A6	Average Actual Assembly Time (A_{av}) Calculation (Sequence 5)	228
A7	Average Actual Assembly Time (A_{av}) Calculation (Sequence 6)	229
B1	Convergence graph: Min Assembly Time 499.900 unit, 10 particles 5000 Iterations, optimized sequence: 2-1-4-9-3-12-5-15-13-18-6-16-11-7-8-14-10-17-19	231
B2	Convergence graph: Min Assembly Time 512.70 unit, 10 particles 3000 Iterations, Optimized sequence: 1-2-4 -9-3-15-16-12-13-18-5-11-6-7-8-14-10-17-19	232
B3	Convergence graph: Min Assembly Time 511.100 unit, 10 particles 800 iterations, optimized sequence: 2-1-4-3 -12-11-9-5-15-13-18-6-7-16-8-10-14-17-19	233
B4	Convergence graph: Min Assembly Time 510.700 unit,	

	40 particles 800 Iterations, Optimized sequence: 1-15-2-4 -18-9-3-12-13-11-5-6-16-7-8-14-10-17-19	234
B5	Optimal results obtained	235
B6	Convergence graph: min. assembly time 496.700 units, 50 particles 8000 Iterations, Optimized sequence: 2-1-4 -9-12-3-13-16-5-15-18-11-6-7-8-10-14-17-19	236
B7	PSO convergence with swarm size 100 particles in 20 runs.	237
B8	Results of Binary PSO with 40 Particles 500 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42 .	238
B9	Results of Binary PSO with 50 Particles 500 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42.	243
B10	Results of Binary PSO with 60 Particles, 500 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42.	248
B11	Results of Binary PSO with 20 Particles, 2000 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42.	253
B12	Results of Binary PSO with 60 Particles, 2000 iterations, inertia weight (0.6), cognitive coefficient (c_1) =1.42, and social coefficient (c_2) = 1.42.	258
C1	Particle Swarm Optimization (PSO) to Optimize an Assembly Sequence Time	264
C2	Binary Particle Swarm Optimization to Optimize an Assembly Sequence Time	269
C3	Hybrid Algorithm (BPSODE) to Optimize an Assembly Sequence Time	290

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

efficiency and costs. There are products consist of 13 components as illustrated in Figure 1.1.

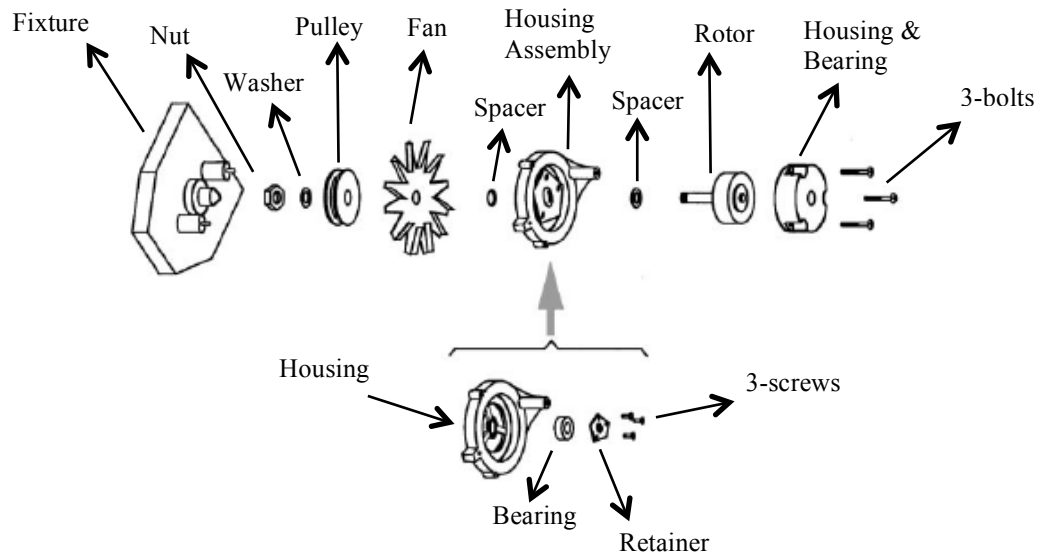


Figure 1.1 An assembly product, which consist of 13 components.
Source: (Hong and Cho, 1999)

The scheduling of production is a complex not perfect process, such that multi-variety, low-batch flow-shop scheduling for makespan minimization become extreme complex and become progressively sophisticated as hundreds of components were engaged (Hejazi and Saghaian, 2005; Kemal et al., 2007). The biggest part of manufacturing workload is assembly. Incorporating design, planning, production, and procurement lead to improvement of product development process by cutoff the time and cost of the developed product. The product order of assembly is the main focus of ASP to determine, which is subjected to a precedence constraint matrix (PM) that is to be strictly followed in the assembly line to shorten the assembly time and concequently minimizing the assembly cost.

1.2 Problem Statement

Sequence planning is an important problem in designing an assembly line. It is to determine an order of assembly tasks to be performed sequentially. The time

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.

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