Modeling and Optimization of Aggregate Production Planning - A Genetic Algorithm Approach

B. Fahimnia, L.H.S. Luong, and R. M. Marian

***Abstract*—**The Aggregate Production Plan (APP) is a schedule of the organization's overall operations over a planning horizon to satisfy demand while minimizing costs. It is the baseline for any further planning and formulating the master production scheduling, resources, capacity and raw material planning. This paper presents a methodology to model the Aggregate Production Planning problem, which is combinatorial in nature, when optimized with Genetic Algorithms. This is done considering a multitude of constraints of contradictory nature and the optimization criterion – overall cost, made up of costs with production, work force, inventory, and subcontracting. A case study of substantial size, used to develop the model, is presented, along with the genetic operators.

***Keywords*—**Aggregate Production Planning, Costs, and Optimization.

I. Introduction

AGGREGATE Production Plans (APP) concern about the allocation of resources of the company to meet the demand forecast. Optimizing the APP problem implies minimizing the cost over a finite planning horizon. This can be done by adjusting production load as well as inventory and employment levels over a certain period of time to achieve the lowest cost while satisfying demand and considering the specific constraints for each particular case (company dependent). A good APP has the capacity to positively influence the bottom line and also permit a long-term view of the organization performance. This avoids having to make short-term decisions and fire-fight problems, adversely affecting the organization's long term perspective [1].

Managers have access to the break-down monthly or weekly demand forecast for the next planning horizon, normally 1 year. In practice, managers capitalize on the forecasted demand to achieve long-run profitability. They face major constraints in the number of workers, facilities and plant capacity to fulfill the demand. Therefore, not only all the demand must be met in each planning period (month/week), but costs have to be minimized. Managers may decide if meeting market demand results in lower long-term profit, to backorder and/or ask the subcontractors to do a part of the products. The APP problem deals with how to employ the available workforce, resources and facilities, including external contractors, to best satisfy the demand which is defined through APP [1].

Although a number of production planning approaches have been developed in order to improve planning automation and increase efficiency of production planning [2], but a lot of problems in the area of production planning are subject to highly complex constraints which make them very difficult to solve using traditional optimization methods and approaches. Despite the importance of APP which forms the basis for the formulation for all other schedules and materials management, the results of the APP optimization are far from perfect, leaving way to major improvements.

This paper uses Genetic Algorithm (GA), and presents an optimization approach to APP modeling, which permits the search for an optimum, while considering, simultaneously, a large number of constraints of contradictory nature. A realistic case study illustrates the model and the development of the GA to an APP problem with the conditions found in an industrial context is presented.

II. Literature Review

The APP problem considering minimum changes in workforce level as well as inventory and backorders minimization simultaneously was solved for an 8-period planning horizon [3]. In 1998, the APP problem was solved using Mixed Integer Programming and considering different optimization criteria, including revenue maximization as well as inventory, backorder and set-up cost minimization [4]. Baykasoglu added further constraints to the previous models such as subcontractor selection and set-up decisions [5].

Later on, a number of artificial intelligence approaches, alone or combined with mathematical programming models have been used to solve the production planning problems

Paper submitted for review on August 29, 2006. This research is conducted as Mr. Fahimnia's master thesis at the University of South Australia, School of Advanced Manufacturing & Mechanical Engineering.

Behnam Fahimnia is a PhD candidate at the University of South Australia, School of Advanced Manufacturing & Mechanical Engineering. Mawson Lakes Campus, SA 5095, Australia (phone: 0061-8-82605176; fax: 0061-8-83023380; e-mail: behnam.fahimnia@postgrads.unisa.edu.au).

Prof. L H S Luong is the head of school and a lecturer at the University of South Australia, School of Advanced Manufacturing & Mechanical Engineering. Mawson Lakes Campus, SA 5095, Australia (e-mail: lee.luong@unisa.edu.au).

Dr. Romeo M. Marian is a lecturer and program director at the University of South Australia, School of Advanced Manufacturing & Mechanical Engineering. Mawson Lakes Campus, SA 5095, Australia (e-mail: romeo.marian@unisa.edu.au).

considering more constraints. GA, fuzzy logic and stochastic programming have been among the most popular ones. Among all, Wang and Fang proposed a fuzzy programming model to imitate the human decision procedure for production planning ended with a family of inexact solutions within an acceptable level [6]. A fuzzy multi-objective linear programming model for solving the multi-product APP decision problem in a fuzzy environment considering inventory level, labor levels, capacity, warehouse space and the time value of money is presented in [7]. A model to optimize the multi-site APP problem by considering a wider range of constrains describing a two-stage stochastic programming model [8].

However, little attention has been given to develop a strategy taking into account the many constraints and their combination, as they appear in practice. The combination of factors simultaneously affecting the quality of the APP is a characteristic of real-life problems and their consideration can make the difference between a purely academic treatment of the subject and a result that can be applied or transferred immediately in practice.

In this paper, a complex and realistic mathematical model is built and a GA is developed for its optimization. It goes beyond developing heuristics to solve simple strategies to optimize the APP. Instead, the approach is general, all optimization constraints are implemented into the Fitness Function and a penalty is incurred for any suboptimal solution. The model contain a large number of practical constraints including production cost, labor cost, hiring and laying off costs, holding costs (carrying inventory during plan period) and subcontracting costs.

III. Research Methodology

In developing the methodology for modeling and optimizing the APP a number of strategies can be and were considered:

Strategy 1: fill the requirements using overtime – workers (all or them or only veteran personnel – workers with at least one week stage in the company) are used to work for an integer number of hours. In this case the inventory and contracting out the units to be delivered are underutilized/disregarded;

Strategy 2: fill the un-met requirements using external contractors – is a lean, outsourcing strategy in regards to keeping inventory, reducing, at the same time the workforce available to a minimum;

Strategy 3: fill requirements using up to the equivalent of a given number of weeks output in inventory, by minimizing at the same time the variation of workforce. This strategy can also minimize the use of contractors, taking advantage properties of keeping inventory to increase or keep a service level [9].

Other strategies or any linear combinations of strategies can be developed and the results of their application assessed. These strategies can be implemented as heuristics in algorithms to optimize the planning process. However, any of these strategies is likely to produce desired results – i.e. minimum costs - only for a narrow combination of conditions and input values, which might appear briefly, as windows - during the planning horizon. The use of any set strategy would, in this case, be suboptimal in the rest of the planning horizon.

Also, it became obvious that, by using a set strategy, there would be a set relation between a number of variables (see next section) e.g. production plan in a period, number of veteran and new workers, the production, hours worked, inventory each day and cumulative inventory and the respective costs.

After examining the results of implementing the strategies presented above, it emerged that a better approach would be to avoid constraining the planning to just one of these strategies. The independent variables in this case are chosen as the number of workers each planning period and the number of hours worked, with all production and inventory levels derived from this. The only constraint imposed is the maximum level of inventory, which is a sensible condition in practice.

It was decided to use the evolutionary character of GA to determine an optimum result by exploring the whole search space. This is the equivalent of finding the best strategy or combinations of strategies at any point in time, and varying it, as necessary, to produce an optimum result. When choosing GA for the optimization process, an important element was their capacity to implement any cost function [10].

IV. Modeling of the APP Problem

As a realistic model is sought for the APP problem, a complex combination of conditions is applied. The list of variables is by no means exhaustive, but it incorporates many decisions variables, economies of scale, hard constraints and costs, etc.

A. *Variables:*

Planning data:

- T - Planning horizon;
- D_Y - Total forecasted demand in year (units/year);
- t - Each period of time in the planning horizon – granularity of the model;
- N_w - Normal working time per week for the company (h);
- D_{Pt} - Forecasted demand for each period in the planning horizon (units/t);
- D_{Ptmin} - The minimum forecasted demand for each period in D_Y (units/t);
- D_{Ptmax} - The maximum forecasted demand for each period in D_Y (units/t);
- P_t - Production of current week (units/week);

Labor costs:

- C_{RL} - Regular wage – including overheads ($/h)
- C_{OL} - Overtime wage – including overheads ($/h)
- T_L – Normal working time per worker per shift
- P_L - Productivity of a veteran worker (units/h)
- P_{NL} - productivity of a new worker in first week (units/h)

L_t - number of full-time permanent labors in period t – variable;
Personnel policy:
C_H - The cost of hiring one labor ($ / Labor)
C_L - The cost of laying off one labor ($ / Labor)
Plant running costs:
N – Actual hours company works per week - variable;
C_P - Plant running cost per hour – normal hours ($/h)
C_{PO} - Plant running cost per hour – overtime ($/h)
Inventory policy:
I_t – inventory level;
C_I - inventory cost to hold a single unit of product at the end of each period ($ / unit - period);
C_S - shortage cost per unit associated with subcontracting ($/unit);

B. Constraints

The assumptions listed below are implemented as a list of feasibility constraints. Violating any of these constraints would produce an infeasible solution:

1. The company works at least N_w hours each week;
2. The number of hours worked in a week is integer;
3. A worker will only produce an integer number of units per week. If the worker cannot produce a whole unit, he/she will be reassigned during that time for maintenance work (paid – equivalent cost for the time worked - but no direct output is obtained);
4. The company has to deliver all products corresponding to the demand each week (service level 100%);
5. The company uses the products made/kept/contracted out to satisfy demand in the following order:
   A. units made that week by the workforce;
   B. the shortage will be covered, if possible, from inventory;
   C. if the company is still short of units, they will be outsourced to contractors;
6. All excess products will be stored in inventory;
7. In the first week of the planning horizon, the company has a number of workers and a number of items in storage in inventory equal with the average number of workers per week to fulfill average demand and the equivalent of an average week of production, respectively;
8. The capacity of the warehouse storing the inventory is maximum three times the average weekly output;

The assumptions above, very realistic in any manufacturing context, have also the potential to significantly simplify the modeling of the problem and the implementation of the algorithm.

It is important to point out that assumption 5 in combination with assumption 8, in fact, guide the decisions regarding the make-or-buy of products or, on the other hand, rely on your work force or adopt a very flexible hire-or-fire policy for employed personnel. As it is set, it tends to favor the existing workforce, with contracting out used only as a last resort. However, this set of assumptions can be modified to be aligned with the management's general strategies and the company's external context.

V. Chromosome Encoding

The chromosome encoding is presented with relation to the case study below. The chromosomes encode the solutions of the problem, in this case assembling the independent variables of the problem – namely the number of workers employed and the number of hours worked each period. The planning horizon was chosen 1 year with a granularity of the model of 1 week. This implies the chromosome is an array of 52 x 2 variables (104 independent variables).

The chromosome is illustrated in Fig. 1 part A, in a vertical format for space-saving purposes. For reference, the number of the week is displayed at the left of the chromosome. The number of hours worked is minimum 80, as explained in the previous section and set in the case study.

VI. The Genetic Algorithm

The structure of the GA is classic [10], with genetic operators adapted to the particularities of the problem. Instead of working with strings, they are tailored to work with arrays. They are illustrated in the following sections.

1. Handling Constraints

The probability to obtain an infeasible chromosome by random genetic operators (GO) is reduced as long as the operators are implemented correctly, taking into account the set of constraints detailed in Section 4. The major source of infeasibility is constraint 8. A chromosome has to be tested for feasibility after generation or application of a GO (crossover or mutation). The repair strategy proposed and tested successfully checks the level of inventory and, if constraint is not satisfied, to reduce the number of workers at the point of infeasibility (for the week when the inventory level exceeds three times the average weekly output) until the gene becomes feasible. Even if rare, it is possible to have more than one infeasible gene in a chromosome. In this case, the repair is to be done successively, from the first to the last week.

2. Crossover

The crossover is, in principle, a simple cut and swap operation. Figure 1 part B presents an example of crossover. In this example, parents P1 and P2, randomly selected from the initial operation, undergo the crossover. The cut point is randomly selected after week 13, and the two bottom-parts of the parents' genetic information are exchanged. After the operation, a feasibility check/repair is necessary.

3. Mutation

The mutation operator is, again, classic in its principle. An example of mutation operator is presented in Figure 2 part B (M1 and M2). In this example, a randomly selected chromosome of the population undergoes mutation. The genetic information from weeks 15 and 39, randomly selected, is swapped. After mutation, the chromosome has to undergo a feasibility check/repair operation.

week	Lt	N	P1		P2		C1		C2	
1	228	80	268	80	214	85	268	80	214	85
2	292	81	217	83	269	81	217	83	269	81
3	158	87	352	87	308	86	352	87	308	86
4	117	86	267	89	317	86	267	89	317	86
5	170	88	377	88	268	84	377	88	268	84
6	336	81	392	81	350	80	392	81	350	80
7	333	87	224	82	308	86	224	82	308	86
8	246	82	205	86	207	89	205	86	207	89
9	215	80	328	82	239	85	328	82	239	85
10	5	82	235	80	297	86	235	80	297	86
11	42	81	360	86	204	82	360	86	204	82
12	163	87	248	82	376	85	248	82	376	85
13	238	87	372	84	320	83	372	84	320	83
14	247	89	349	83	330	80	330	80	349	83
15	73	86	374	83	248	89	248	89	374	83
16	112	80	260	86	204	87	204	87	260	86
17	53	88	344	87	399	87	399	87	344	87
18	337	83	273	81	243	89	243	89	273	81
19	215	84	221	81	204	88	204	88	221	81
20	224	83	355	80	359	83	359	83	355	80
21	76	81	271	83	342	88	342	88	271	83
22	255	80	336	82	313	80	313	80	336	82
23	277	86	398	87	321	88	321	88	398	87
24	116	85	259	87	298	82	298	82	259	87
25	4	87	260	86	278	83	278	83	260	86
26	173	84	254	88	283	84	283	84	254	88
27	129	88	241	82	321	88	321	88	241	82
28	159	80	387	86	381	86	381	86	387	86
29	291	85	332	84	260	85	260	85	332	84
30	288	80	247	89	246	87	246	87	247	89
31	134	85	228	81	266	89	266	89	228	81
32	132	85	340	83	310	80	310	80	340	83
33	27	82	264	81	256	88	256	88	264	81
34	292	88	363	83	274	89	274	89	363	83
35	39	85	285	84	226	86	226	86	285	84
36	309	80	202	85	260	83	260	83	202	85
37	119	82	257	83	344	81	344	81	257	83
38	254	86	321	88	266	88	266	88	321	88
39	379	87	320	83	239	83	239	83	320	83
40	223	83	244	84	329	85	329	85	244	84
41	236	83	355	85	270	83	270	83	355	85
42	379	80	340	83	218	86	218	86	340	83
43	313	84	375	89	346	87	346	87	375	89
44	21	81	212	84	299	89	299	89	212	84
45	161	86	398	85	230	85	230	85	398	85
46	371	83	227	83	243	81	243	81	227	83
47	258	88	203	84	263	87	263	87	203	84
48	217	82	242	83	341	83	341	83	242	83
49	307	86	237	84	328	81	328	81	237	84
50	295	83	218	88	245	82	245	82	218	88
51	236	84	302	88	320	84	320	84	302	88
52	158	86	338	85	368	87	368	87	338	85

A B

Fig. 1 The chromosome and the crossover operators

week	Lt	N	M1		M2	
1	228	80	229	80	229	80
2	292	81	329	80	329	80
3	158	87	393	86	393	86
4	117	86	296	89	296	89
5	170	88	361	86	361	86
6	336	81	257	86	257	86
7	333	87	216	80	216	80
8	246	82	333	87	333	87
9	215	80	399	80	399	80
10	5	82	219	87	219	87
11	42	81	250	82	250	82
12	163	87	343	89	343	89
13	238	87	374	86	374	86
14	247	89	311	88	311	88
15	73	86	398	85	211	86
16	112	80	291	84	291	84
17	53	88	305	87	305	87
18	337	83	216	88	216	88
19	215	84	393	89	393	89
20	224	83	296	84	296	84
21	76	81	297	82	297	82
22	255	80	325	86	325	86
23	277	86	320	85	320	85
24	116	85	369	81	369	81
25	4	87	221	84	221	84
26	173	84	290	83	290	83
27	129	88	248	84	248	84
28	159	80	273	83	273	83
29	291	85	388	86	388	86
30	288	80	345	89	345	89
31	134	85	240	84	240	84
32	132	85	312	84	312	84
33	27	82	233	85	233	85
34	292	88	390	80	390	80
35	39	85	211	86	398	85
36	309	80	362	82	362	82
37	119	82	260	87	260	87
38	254	86	317	89	317	89
39	379	87	222	86	398	85
40	223	83	258	82	258	82
41	236	83	378	80	378	80
42	379	80	242	81	242	81
43	313	84	400	87	400	87
44	21	81	356	87	356	87
45	161	86	380	83	380	83
46	371	83	210	88	210	88
47	258	88	258	86	258	86
48	217	82	399	87	399	87
49	307	86	356	82	356	82
50	295	83	375	88	375	88
51	236	84	247	88	247	88
52	158	86	225	80	225	80

A B

Fig. 2 The chromosome and the mutation operator

4. Evaluation

The Fitness Function (FF) of each chromosome is dependent upon the costs associated with the application of the strategy associated with the corresponding particular solution. GA has a remarkable ability to incorporate and use almost any conceivable type of cost structure [10], [11]. The total cost (TC) for a solution/chromosome is the sum of all costs attached to operating the company for the next forecasting horizon:

$$TC = \sum_{i=1}^{52} (PC + WC + IC + SC)$$

PC - Production cost – takes into account the normal and overtime rate;

$PC = C_P \quad \text{if } N \le N_W;$

$PC = C_{PO} \quad \text{if } N \ge N_W$

WC - Costs associated with workforce

$WC = WC1_t + WC2_t$

WC - made of wages (WC1) + hiring and firing costs (WC2);

$WC1 = N * L_t * C_{RL}$ if $N \le N_W$; - normal working time
$WC1 = L_t * N * C_{RL} + L_t * (N_w * N * CO_L$ if $N \ge N_W$; - if overtime is needed

$WC2 = C_H * (L_t – L_{t-1})$ if $L_t \ge L_{t-1}$ - if workers hired
$WC2 = C_L * (L_{t-1} – L_t)$ if $L_t < L_{t-1}$ - if workers fired

IC – Inventory keeping costs –only if inventory is positive;
$IC = (I_{t-1} + P_t + D_{Pt}) * C_I$ if $IC \ge 0$
IC = (Previous week inventory + Production of current week – Forecasted demand) * inventory keeping costs;

Where
I_{t-1} – previous week's inventory – given for first week, calculated subsequently;
$P = N * L_t * P_L$ if $L_t \le L_{t-1}$ – production by veteran workers
$P = (N * L_{t-1} * P_L) +N * (L_t – L_{t-1}) * P_{NL}$ if $L_t > L_{t-1}$ – production by veteran workers and newly hired workers.
D_{Pt} - forecasted demand for each period in the planning horizon (units/t) - given;

SC – Costs associated with subcontracting a part of production;
If IC, calculated as above is negative, it has to be covered by subcontracting:
If $IC < 0$, $SC = IC * C_S$

5. Selection

The stochastic sampling mechanism is used to select the next generation of chromosomes, associated with the Holland's proportionate selection or roulette wheel selection (Holland, 1975). Because the weighed roulette works for maximization of the fitness values and the GA in this case is designed to minimize the cost, a simple double transformation is applied: the inverse solutions' cost is multiplied with 10^{10}. After the GA has been applied, the true costs are restored, using the inverse operation – i.e. multiplying the inverse of the FF with 10^{10} [12].

VII. A Case Study

A case study has been developed in conjunction with the model presented in last sections. The forecast for the next year is broken down in Table I. The case study is based on the following data and has co-evolved with the model of the APP problem:

TABLE I
WEEKLY DEMAND FOR THE PLANNING HORIZON

Week	Demand	W	D	W	D	W	D
1	12000	14	9500	27	10500	40	10000
2	10500	15	11000	28	11000	41	10000
3	8000	16	10000	29	11000	42	9500
4	11500	17	10500	30	11500	43	8000
5	8000	18	11000	31	10500	44	10500
6	10000	19	10000	32	8500	45	10500
7	9000	20	9500	33	10500	46	8500
8	10500	21	10000	34	9500	47	11000
9	11500	22	11000	35	8500	48	9000
10	12000	23	12000	36	10000	49	8500
11	8000	24	8000	37	8000	50	8500
12	11000	25	9000	38	11500	51	11000
13	8500	26	12000	39	10000	52	10000

T = 1 year;
D_Y = 520000 units;
t = 1 week;
N_w = 80h/week (two 8 hour shifts per day, 5 days/week);
D_{Pt} = forecasted demand for each period in the planning horizon (units/t) – in Table 1;
D_{Ptmin} = 8000 units;
D_{Ptmax} = 12000 units;
P_r = 130 units/h;
C_{RL} = \$ 20/h;
C_{OL} = = \$ 30/h;
T_L = 40 h/week;
P_L = 1 unit/h;
P_{NL} = 0.7 unit/h;
C_H = \$ 800;
C_L = \$ 1500;
C_P = \$ 2600/h;
C_{PO} = \$3900/h;
C_I = \$ 10 per week per unit;
C_S = \$ 80/unit up to 100 units/week;
C_S = \$ 60/unit over 100 units/week;

The values presented above were used to develop and test the genetic operators. The cost function is implemented as a subroutine composed of the relevant cost modules. The cost structure is flexible and can be easily modified to suit any similar problem if necessary, since constraints can be varied in magnitude and other constrains can be added as required.

VIII. Conclusion

A complex and realistic model for the optimization of the APP has been developed. It incorporates the most important constraints and costs currently encountered in a manufacturing company.

The GA for the optimization of the APP is in an advanced implementation state. All operators have been developed and tested and will be integrated in the full algorithm shortly. Preliminary results are promising.

Further work will address the following:
- Finalization of the full GA and its testing;

- Implementation of a yet more complex cost structure, ideally by developing a framework to incorporate all realistic costs that can appear in practice;
- Optimality of results and how they are influenced by the relative level of different classes of costs on the strategy to employ, patterns of strategies as the level of costs vary;
- The possibility to address stochastic events and their influence on the optimality of the APP.

ACKNOWLEDGMENT

As the first author of this paper, I am indebted to Dr. Romeo Marian and Prof. Lee Luong for their positive influence in conducting this research. I am also very much grateful to my dear brother, *Mr. Behdad Fahimnia*, and whole family members for their all-time supports and I dedicate this research to them all. I hope this study can add to the body of knowledge in Manufacturing.

REFERENCES

[1] Meredith, J. R. & Shafer, S. M. "Operations Management for Mbas", John Wiley & Sons Inc., New York, 2001.
[2] Tempelmeier, H. & Kuhn, H. "Flexible Manufacturing Systems: Decision Support for Design and Operation", Wiley, New York, 1993.
[3] Masud, A. S. M. & Hwang, C. L., "An Aggregate Production Planning Model and Application of Three Multiple Objective Decision Methods", International Journal Of Production Research, 18, 741 - 752, 1980.
[4] Y. F. Hung, & Y. C. Hu, "Solving Mixed Integer Programming Production Planning Problems With Setups By Shadow Price Information", Computer Operations Research, 25, 1027-1042, 1998.
[5] A. Baykasoglu, "Aggregate Production Planning Using the Multiple-Objective Tabu Search", Int J Prod Res, 39, 3685-3702, 2001.
[6] Wang, D. & Fang, S. C. "A Genetics-based Approach for Aggregated Production Planning in a Fuzzy Environment". Ieee Transactions On Systems, Man, And Cybernetics, Part A: Systems & Humans, 27(5), 1997.
[7] Wang, R. C. & Liang, T. F. "Application of Fuzzy Multi-Objective Linear Programming to Aggregate Production Planning", Pergamon Press Inc, 2004.
[8] Leung, S. C. H., Wu, Y. & Lai, K. K. "A Stochastic Programming Approach for Multi-Site Aggregate Production Planning". Journal of the Operational Research Society, 57, 123 – 132, 2005.
[9] Simchi-Levi, D., Kaminsky, P. & Simchi-Levi, E. "Designing and Managing the Supply Chain: Concepts, Strategies and Case Studies", Mcgraw-Hill Publishers, New York, 2003.
[10] M. Gen, & R. Cheng, "Genetic Algorithms and Engineering Optimization", Wiley, New York, 2000.
[11] Marian, R. M. "Optimization of Assembly Sequences Using Genetic Algorithms", Advanced Manufacturing and Mechanical Engineering, Adelaide, Australia, University Of South Australia, 2003.
[12] Marian, R. M., Luong, L. H. S. & Akararungruangkul, R. "Optimization of Distribution Networks Using Genetic Algorithms", Part 2, The Genetic Algorithm and Genetic Operators, International Journal of Manufacturing and Technology Management, Accepted, In Press, 2006.

Mr. Behnam Fahimnia was born in Tehran, the capital city of Iran, in 1978. He graduated with bachelor degree in Mechanical Engineering, Solids Designing from **Tehran Azad University** in 2001 ranked 2nd and granted the university fellowship in 1999. At present, he is in the completion of a master program in Advanced Manufacturing Technology at the **University of South Australia**. Mr. Fahimnia ranked the top student with High Distinction in all subjects and is now in the process of joining the PhD program late 2006.

He has published several papers in national and international conferences and the most recent ones are listed bellow:

- B. Fahimnia, R. Marian, B. Motevallian, M. Mohammad Esmaeil, & K. Abhary, "A heuristic method to optimize manufacturing lead time", to be published in *the 17th International DAAAM Symposium*, Austria, Vienna, 2006.
- B. Fahimnia, L. H. S. Luong, M. Mohammad Esmaeil, B. Motevallian, & R. Marian, "The negative impacts of globalization on local manufacturing", to be published in *the 17th International DAAAM Symposium*, Austria, Vienna, 2006.

He is also a research assistant at the University of South Australia, School of Advanced Manufacturing and Mechanical Engineering, under supervision of Dr. Romeo Marian. His research interests are Production Planning, Project Planning and Control, Manufacturing Automation, Genetic Algorithms.

Mr. Fahimnia is a member of Institute of Engineers Australia (IEAus), Australia, and Institute of Mechanical Engineers (IMechE), UK. He is now registered as a professional engineer in Australia and is a registered employee at the University of South Australia, with the School of Advanced Mechanical and Manufacturing Engineering.

