A PSO Based Goal Programming Approach to Aggregate Planning of Production, Workforce, and Pricing Strategy

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Abstract: Aggregate production planning (APP) is medium-range planning and generally needed when demand is highly seasonal. Most APP models consider constant demand, which would limit their usefulness. An attempt is made in this study to also take the pricing strategy into consideration because of its major influence on demand. The proposed model describes the maximization of both revenue and profit that may conflict one another. Thus, constrained nonlinear multiple objectives optimization model is developed. Goal programming by using an evolutionary stochastic algorithm, particle swarm optimization (PSO), is investigated for the formulated problem because of the PSO’s simplicity, speed, and robustness. Due to the complexity of the derived constraints, penalty function method and some heuristics are incorporated with the PSO algorithm to handle them. The results are examined to assess the performance of both the proposed APP model and the PSO algorithm. Conclusions are drawn and suggestions for the applicability of the PSO algorithm and the APP model are also given.

Keywords: Aggregate Production Planning, Goal Programming, Particle Swarm Optimization, Penalty Function Method

1. INTRODUCTION

Aggregate production planning (APP) or macro production planning determines the resource capacity needed to meet demand such as size of workforce, inventory levels, and regular and overtime production. It is medium-range planning and generally needed when demand is highly seasonal. Most APP models consider constant demand, which would limit their usefulness. An attempt is made in this study to take the pricing strategy into consideration because of its major influence on demand. Generally, demand is low if the price is high. The opposite is also true. Hence, a linear relationship between product price and product demand is assumed in this work. In APP, the goal is to determine a final plan of related factors in each period over an intermediate time horizon. This can be accomplished through various goals at the same time. The primarily ones are maximization of profit, maximization of revenue to gain market share, or maximization of both profit and revenue. Goal programming approach provides a way of striving toward more than one objective simultaneously.

Most APP models can be formulated as linear programming problems but this is not the case for the proposed model. This warrants an opportunity of application for near-optimal heuristics to solve this multiple objectives optimization problem. In this study, particle swarm optimization (PSO), a relatively new approach for solving optimization problem, is employed to solve the proposed APP problem due to its simplicity, speed, and robustness. The PSO allows a group of particles to search for the solution. Knowledge gained by each agent is shared among one another in order to iteratively find an improved solution.

In this paper, a multiple objective APP for single production line is taken into consideration. Size of workforce, inventory levels, and regular and overtime production are determined to maximize profit, maximize revenue, and maximize revenue while holding the profit to at most 5 %, 10 %, or 15 % lower than the maximum profit. In the last case, goal programming approach is applied by using a constrained PSO algorithm. In Section 2, related literatures are reviewed. Section 3 presents the formulation of the proposed APP model. A brief discussion of the PSO is presented in Section 4. Section 5 presents results and discussion. The final section, Section 6, concludes the research experiment conducted.
2. LITERATURE REVIEW

2.1 Aggregate Production Planning

APP is the problem to determine the resource capacity needed to meet demand in the production line. Many researchers have studied to solve this type of management problems. Linear programming model with linear cost structure was proposed by Hanssman and Hess (1960) to schedule production and employment. Similarly, linear decision rule (LDR) was presented by Holt et al. (1956). Multiple regression was also used to determine proper coefficients of APP decision model (Bowman, 1963). Vergin (1966) proposed a search-base simulation model. Parametric production planning (PPP) model with an objective function describing the cost structure of a firm was formulated and solved by Jones (1967). Some heuristic optimization techniques have been developed to solve APP problems. A search decision rule (SDR) was developed to generate an acceptable solution for APP (Taubert, 1968). Mellichamp and Love (1978) presented the adaptable production switching heuristics (PSH) model whose results were quite consistent with the actual managerial practices.

The newer works included the use of spreadsheet software to solve APP problems in easier accessible way (Shafer, 1991; Albright et al., 1999; Techawiboonwong and Yenradee, 2002; Techawiboonwong and Yenradee, 2003). Multiple objectives APP have gained more interest lately due to its close resemblances to the real situations. Das et al. (2000) integrated APP, master production scheduling, and short-term production scheduling to a common data model. Multiple-criteria linear programming was also used to solve an APP model subject to a set of constraints (Masud and Hwang, 1980). Fuzzy numbers were incorporated into multiple objectives APP with uncertainty of demand forecasts (Wang and Fang, 2001). Da Silva et al. (2006) developed a decision support system with multiple objectives for APP models.

Some metaheuristic algorithms were also employed to solve APP problems. Stockton and Quinn (1995) proposed a genetic algorithm based method for solving an APP problem. Wang and Fang (1997) applied genetic algorithm (GA) based method with fuzzy logic to imitate the human decision procedure. Instead of locating exact optimal solution, this algorithm searched for a family of inexact solutions within acceptable level. Then, a final solution was selected by examining a convex combination of these solutions. Kumar and Haq (2005) solved an APP problem by using ant colony algorithm (AGA), genetic algorithm (GA), and hybrid genetic-ant colony algorithm (HGA). From the outcomes obtained, GA and HGA showed comparably good performance.

2.2 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a metaheuristic optimization for continuous problems. It was developed by imitating social behavior of bird flocking, fish schooling, and swarming theory (Eberhart and Kennedy, 1995; Kennedy and Eberhart, 1995). It embeds some mechanisms that are quite robust and can avoid local optima trap. Moreover, its evaluating function does not have to be twice differentiable. These make the PSO very attractive as one of the most efficient and effective optimization algorithm. Furthermore, the PSO is very easy to implement with few lines computer code. It has been applied to solve a wide variety of applications. El-Mounayri et al. (1998; 2003) used PSO to predict parameters of surface roughness in end milling. Prakashvudhisarn (2004) used PSO to determine minimum tolerance zones of all basic form features for discrete parts inspection.

The PSO was also extended to solve discrete problems. Kennedy and Eberhart (1997) modified PSO to handle discrete binary variables. Experiments were conducted on standard test functions. The obtained outcomes showed that the PSO still performed well in terms of quality of solutions, robustness, and speed. Later, PSO was applied to other discrete problems including lot sizing problem (Tasgetiren and Liang, 2003), flow-shop scheduling (Lian et al. 2006), and traveling salesman problem (Pang et al., 2004; Wang et al., 2003).

Some researchers applied PSO to solve optimization problems with constraints. Hu et al. (2002; 2003) modified the PSO to solve constrained nonlinear problems by preserving only feasible solutions. In this method, the PSO checks whether the current particle violates any constraints or not. If none of constraints is violated, mechanisms of PSO will continue normally. Otherwise, a wasted iteration occurs. This will loop until a feasible solution is found. Another widely used method for solving constrained optimization problems was done by adding a penalty term of the violated constraint to the original objective function (Parsopoulos and Vrahatis, 2002). Generally, degree of penalty was dependent on significance of constraint violation.

3. AGGREGATE PRODUCTION PLANNING FORMULATION

3.1 Mathematical notation of the proposed aggregate production planning model

\( m \) represents number of planning periods,
\(N(t)\) represents number of normal workdays in period \(t\),
\(RH\) represents number of regular working hours in each normal workday,
\(MINW\) represents minimum number of workers required to operate production line,
\(MAXW\) represents maximum number of workers required to operate production line,
\(K\) represents average production rate of product per day,
\(MAXI\) represents maximum allowable inventory level of product,
\(CW\) represents average salary per month for each worker in production,
\(CM\) represents material costs of one unit of product,
\(CH\) represents hiring cost per worker in production line,
\(CL\) represents lay-off cost per worker in production line,
\(CI\) represents average inventory holding cost per period per unit of product,
\(CON\) represents overtime cost per man hour during normal workday for production line,
\(CF\) represents fixed costs of production per time period,
\(QD(t, PRICE(t))\) represents quantity demanded of product as function of price in period \(t\).

Decision variables included in the model are as follows:
\(PRICE(t)\) is price of product in period \(t\),
\(QS(t)\) is quantity of product sold in period \(t\),
\(W(t)\) is number of workers working in production line at time \(t\),
\(H(t)\) is number of workers hired to production line at beginning of period \(t\),
\(L(t)\) is number of workers fired from production line at beginning of period \(t\),
\(ON(t)\) is overtime man hours for producing product during overtime in period \(t\),
\(U(t)\) is undertime (idle time) man hours of workers in production line in period \(t\),
\(P(t)\) is total production quantity of product in period \(t\),
\(I(t)\) is inventory level of product at the end of period \(t\).

3.2 Aggregate production planning model

3.2.1 Quantity demand (QD)

The proposed APP model in this study is based on the model presented by Techawiboonwong and Yenradee (2003) but only single production line is considered. In addition, modification on quantity demand (QD) is adopted. The model is assumed according to basic microeconomic theory, instead of considering only constant demand in each period of APP, linear demand QD is suggested. Generally, with linear QD, the buying pattern of consumers is inversely proportional to the selling price of the product. The higher the product price, the lower the product demand. A simple linear function used to determine QD in each period \(t\) according to price in period \(t\) can be described:

\[
QD(t, price(t)) = -\frac{(p(t) - q(t))}{(\bar{p}(t) - \bar{q}(t))(PRICE(t) - \bar{p}(t)) + \bar{q}(t)}
\]

where \(\bar{p}(t)\) is high price in period \(t\),
\(\bar{p}(t)\) is low price in period \(t\),
\(q(t)\) is high demand in period \(t\),
\(q(t)\) is low demand in period \(t\).

3.3.2 Objective functions

In this APP model, three goals are taken into account. The first one is to maximize profit. This is the primary goal of most business firms. This objective is accomplished by maximizing the difference between total revenue and total cost of every period. Seven types of costs are taken into consideration including worker salary, hiring cost, firing cost, overtime cost, material cost, inventory cost, and fixed cost. Thus, the objective function for profit maximization can be written as:
The second goal is to maximize revenue. This implies the maximization of the firm’s market share. Even though this is not the main goal, it is quite important for management depending on its strategy, position of the firm in the industry, competitors’ status, and economic situation. This objective can be calculated by maximizing the revenue, which is the product of product price and quantity sold, in every period $t$. Hence, the revenue maximization can be expressed as:

$$\text{MAX} : \sum_{t=1}^{m} \text{PRICE}(t) \times QS(t)$$

(3)

Normally, the goals of reaching the greatest revenue and profit may not individually drive the firm into the same direction. Consideration of only one factor would definitely misinform management and the decision made may not cover the entire situation encountered by the firm. Therefore, both factors, profit and revenue, should be taken into consideration together. This leads to the third goal of this study, which is the maximization of both profit and revenue simultaneously. This is called a multiple objective optimization problem and can be handled by using a goal programming approach. The small percentage reduction (PERC) of profit is introduced as a lower bound in the formulation from maximum profit while maximizing revenue. Hence, this profit reduction is treated as an additional constraint in the APP model. The selection of PERC values depends on management strategy. If the market share is of main concern, PERC is set to a rather high value. In this study, three different PERC values are experimented as discussed below.

3.3.3 Constraints for quantity sold

The quantity of product sold in period $t$ cannot exceed the quantity of product demanded in the same period. Thus, the quantity sold constraints in each period $t$ can be written as:

$$QS(t) \leq QD(t, \text{PRICE}(t))$$

(4)

3.3.4 Production constraints

The number of units produced in period $t$ depends on regular production, overtime production, and undertime (idle time) of workers. Hence, production constraints can be written as:

$$P(t) = K \times W(t) \times n(t) + \frac{K}{RH} \times ON(t) - \frac{K}{RH} \times U(t)$$

(5)

3.3.5 Inventory constraints

Inventory at the end of period $t$ is derived from inventory at the end of previous period $t-1$, production in current period $t$, and the quantity sold in present period $t$. Therefore,

$$I(t) = I(t-1) + P(t) - QS(t)$$

(6)

In addition, the maximum inventory in each period $t$ should not exceed a maximum limit of inventory due to the availability of storage space required.

$$I(t) \leq \text{MAXI}$$

(7)

3.3.6 Worker constraints

The number of workers in period $t$ depends on the number of workers in previous period, and the number of workers hired and fired in current period. Thus,
\[ W(t) = W(t-1) + H(t) - L(t) \]  \hfill (8)

Moreover, minimum and maximum numbers of workers assigned to a production line in each period provide the lower and upper bounds for size of workforce in current period. Hence,

\[ \text{MINW} \leq W(t) \leq \text{MAXW} \]  \hfill (9)

3.3.7 Nonnegativity and integer constraints

All decision variables in APP problem are nonnegative and the number of workers must be integer.

4. PSO AND CONSTRAINED APP PROBLEM

Particle swarm optimization is a relatively new optimization algorithm. This optimization technique imitates social behavior of birds while searching for food. Its main advantages are no requirement for gradient information of the evaluated function, simple and efficient mechanisms for local optima avoidance, quick convergence, and short computer code. As a result, the PSO becomes one of the most efficient and effective optimization algorithms and has been widely utilized in many applications. Steps of the standard PSO are well documented in (Eberhart and Kennedy, 1995; Kennedy and Eberhart, 1995) and not repeated here.

Since the PSO is not built to efficiently and effectively handle constraints, special structures of the proposed APP problem are then utilized to circumvent most constraints. The following simple heuristic is used to convert a constrained to a non-constrained problem. For the proposed APP problem, the PSO is used to search only for the values of \( \text{PRICE}(t), W(t), \) and \( l(t) \) within allowable ranges of each variable. When the \( \text{PRICE}(t) \) is known the demand will be known accordingly. \( H(t) \) and \( L(t) \) are calculated based on \( W(t) \). \( P(t) \) is calculated based on the known values of \( H(t) \) and the demand using equation 6. \( ON(t) \) and \( U(t) \) are then calculated based on \( P(t) \) and \( W(t) \) using equation 5. Note that when the \( P(t) \) exceeds \( K^*W(t)^*n(t) \), the \( ON(t) \) is positive but when the \( P(t) \) is less than \( K^*W(t)^*n(t) \), the \( U(t) \) is positive. Finally, the profit and revenue objective functions are calculated.

For the goal programming approach, the profit maximization problem is solved first. The optimal profit (\( Z^* \)) is allowed to be reduced by some percentage called \( \text{PERC} \). Then, the revenue maximization problem is solved with the additional constraint (10).

The Profit \( \geq (1-\text{PERC}) Z^* \) \hfill (10)

The constraint (10) is handled by the penalty function method. An extra term from constraint (10) is combined with the original objective function. If a constraint violation occurs, its corresponding term then penalizes the combined function. The level of penalty is dependent on the level of violation. Then, the modified objective function is

\[ \text{max } F(x) \]  \hfill (11)

and

\[ F(x) = f(x) - h(k) \cdot H(x) \]  \hfill (12)

where \( f(x) \) is original objective function,
\( h(k) \) is dynamic penalty value in iteration \( k \),
\( H(x) \) is penalty factor.

\[ H(x) = \sum_{i=1}^{r} \theta(q_i(x))q_i(x)^{\gamma(q_i(x))} \]  \hfill (13)

where \( q_i(x) = \max \{0, g_i(x)\} \),
\( \theta(q_i(x)) \) is multi-stage assignment function,
\( \gamma(q_i(x)) \) is power of penalty function,
\( g_i(x) \) is degree of constraint violation.
5. EXPERIMENTAL SETUP AND RESULTS

There are three different time frames considered in this research. There are also three different percentage reductions of maximum profit investigated. Parameters and limits of each variable are summarized in Table 1.

Table 1. Parameters considered in aggregate production planning model.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m$</td>
<td>7, 12, 18</td>
</tr>
<tr>
<td>$n(t)$</td>
<td>20</td>
</tr>
<tr>
<td>$h(t)$</td>
<td>7</td>
</tr>
<tr>
<td>$RH$</td>
<td>9</td>
</tr>
<tr>
<td>$MIN W$</td>
<td>10</td>
</tr>
<tr>
<td>$MAX W$</td>
<td>55</td>
</tr>
<tr>
<td>$K$</td>
<td>50</td>
</tr>
<tr>
<td>$MAX I$</td>
<td>10000</td>
</tr>
<tr>
<td>$CW$</td>
<td>5500฿</td>
</tr>
<tr>
<td>$CH$</td>
<td>1200฿</td>
</tr>
<tr>
<td>$CL$</td>
<td>5000฿</td>
</tr>
<tr>
<td>$CI$</td>
<td>0.2฿</td>
</tr>
<tr>
<td>$CON$</td>
<td>35฿</td>
</tr>
<tr>
<td>$COH$</td>
<td>45฿</td>
</tr>
<tr>
<td>$CM$</td>
<td>80฿</td>
</tr>
<tr>
<td>$CF$</td>
<td>200000฿</td>
</tr>
<tr>
<td>PERC</td>
<td>5, 10, 15</td>
</tr>
</tbody>
</table>

The time period, $t$, is initialized to zero for all parameters related to time. The initial number of workers and inventory are initialized to 30 persons and 1,000 units, respectively. All PSO’s parameters but size of particles, and number of iterations are set according to those experimented in Parsopoulos and Vrahatis (2002). The PSO is implemented by using MATLAB 7.0.4 on Pentium IV 2.8 GHz with 1 GB RAM running Microsoft Windows XP. LINGO, a widely used optimization software package, is also used to solve the same APP problems.

Results obtained from both the PSO and LINGO are summarized in Tables 1-3. PSO’s results are an average of 5 runs with particle size of 2,000 and 2,000 iterations per each run. In the case of 18-period with 5 % PERC (Table 4), the number of particles is raised to 2,500 due to the complexity of the model. The selection of these parameters is proportional to those proposed by Parsopoulos and Vrahatis (2002). They used 100 particles and 1,000 iterations, which worked well with small-sized problems tested. The greatest dimensions attempted were only 7. This is much smaller when compared with the APP problems tackled in this work. The range of dimensions varies from 21 in the smallest model to 54 in the largest model. This in turn dramatically increases the complexity of the problem and its search space. Trial and error approach is then used to choose these parameters.

Profits and revenues obtained by the PSO are reported as the percentage deviation from those of LINGO. Standard deviation (SD) between each run of the PSO is depicted as percentage of mean. A selected final plan is shown in Table 5. This is the final plan of profit maximization for 7 periods.
Table 2. Profits and revenues of aggregate production planning obtained for 7 periods.

<table>
<thead>
<tr>
<th></th>
<th>LINGO</th>
<th></th>
<th>PSO</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profit</td>
<td>Revenue</td>
<td>% Profit deviation (% SD)</td>
<td>Revenue</td>
</tr>
<tr>
<td>Maximize profit</td>
<td>2.41485*10^7</td>
<td>5.523621*10^7</td>
<td>0.14760 (0.09433)</td>
<td>0.18955 (0.38178)</td>
</tr>
<tr>
<td>Maximize revenue</td>
<td>-</td>
<td>6.445833*10^7</td>
<td>-</td>
<td>0.06939 (0.00000)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 5 % PERC</td>
<td>2.294108*10^7</td>
<td>6.004809*10^7</td>
<td>0.000021 (0.00000)</td>
<td>0.00252 (0.00159)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 10 % PERC</td>
<td>2.173365*10^7</td>
<td>6.161406*10^7</td>
<td>-0.00001 (0.00000)</td>
<td>0.00454 (0.00469)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 15 % PERC</td>
<td>2.052622*10^7</td>
<td>6.261298*10^7</td>
<td>-0.00002 (0.00000)</td>
<td>0.01411 (0.02792)</td>
</tr>
</tbody>
</table>

Table 3. Profits and revenues of aggregate production planning obtained for 12 periods.

<table>
<thead>
<tr>
<th></th>
<th>LINGO</th>
<th></th>
<th>PSO</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profit</td>
<td>Revenue</td>
<td>% Profit deviation (% SD)</td>
<td>Revenue</td>
</tr>
<tr>
<td>Maximize profit</td>
<td>4.183974*10^7</td>
<td>9.514605*10^7</td>
<td>0.45517 (0.17226)</td>
<td>-0.37629 (0.21370)</td>
</tr>
<tr>
<td>Maximize revenue</td>
<td>-</td>
<td>1.109958*10^8</td>
<td>-</td>
<td>0.08554 (0.01112)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 5 % PERC</td>
<td>3.974775*10^7</td>
<td>1.036677*10^8</td>
<td>-0.00001 (0.00001)</td>
<td>0.06248 (0.12756)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 10 % PERC</td>
<td>3.765577*10^7</td>
<td>1.062362*10^8</td>
<td>0.00001 (0.00001)</td>
<td>0.05823 (0.05223)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 15 % PERC</td>
<td>3.556378*10^7</td>
<td>1.079011*10^8</td>
<td>-0.00002 (0.00004)</td>
<td>0.04352 (0.04288)</td>
</tr>
</tbody>
</table>

Table 4. Profits and revenues of aggregate production planning obtained for 18 periods.

<table>
<thead>
<tr>
<th></th>
<th>LINGO</th>
<th></th>
<th>PSO</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Profit</td>
<td>Revenue</td>
<td>% Profit deviation (% SD)</td>
<td>Revenue</td>
</tr>
<tr>
<td>Maximize profit</td>
<td>6.448334*10^7</td>
<td>1.456105*10^8</td>
<td>0.97821 (0.27410)</td>
<td>0.30457 (0.60505)</td>
</tr>
<tr>
<td>Maximize revenue</td>
<td>-</td>
<td>1.694688*10^9</td>
<td>-</td>
<td>0.08239 (0.01362)</td>
</tr>
<tr>
<td>*Maximize profit and revenue with 5 % PERC</td>
<td>6.125917*10^7</td>
<td>1.584986*10^8</td>
<td>-0.00003 (0.00003)</td>
<td>0.19630 (0.11861)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 10 % PERC</td>
<td>5.803501*10^7</td>
<td>1.623838*10^8</td>
<td>-0.00001 (0.00003)</td>
<td>0.0952942 (0.093528)</td>
</tr>
<tr>
<td>Maximize profit and revenue with 15 % PERC</td>
<td>5.481084*10^7</td>
<td>1.648697*10^9</td>
<td>-0.00006 (0.00006)</td>
<td>0.06370 (0.05996)</td>
</tr>
</tbody>
</table>

*2,500 particles.
Table 5. A selected final plan from profit maximization for 7 periods.

<table>
<thead>
<tr>
<th>Period</th>
<th>Price</th>
<th>Workforce</th>
<th>Hiring</th>
<th>Firing</th>
<th>Overtime</th>
<th>Undertime</th>
<th>Production</th>
<th>Inventory</th>
<th>Quantity Sold</th>
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<tbody>
<tr>
<td>1</td>
<td>142.18</td>
<td>43</td>
<td>13</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>43,000</td>
<td>4,362.91</td>
<td>39,637.09</td>
</tr>
<tr>
<td>2</td>
<td>156.74</td>
<td>55</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>55,000</td>
<td>10,000</td>
<td>49,362.91</td>
</tr>
<tr>
<td>3</td>
<td>180.52</td>
<td>55</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>55,000</td>
<td>2,423.61</td>
<td>62,576.39</td>
</tr>
<tr>
<td>4</td>
<td>173.65</td>
<td>55</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>55,000</td>
<td>0</td>
<td>57,423.61</td>
</tr>
<tr>
<td>5</td>
<td>162.92</td>
<td>55</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>55,000</td>
<td>0</td>
<td>55,000</td>
</tr>
<tr>
<td>6</td>
<td>148.75</td>
<td>55</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.00</td>
<td>55,000</td>
<td>10,000</td>
<td>45,000</td>
</tr>
<tr>
<td>7</td>
<td>132.08</td>
<td>27</td>
<td>0</td>
<td>28</td>
<td>0</td>
<td>42.35</td>
<td>26,764.71</td>
<td>0</td>
<td>36,764.71</td>
</tr>
</tbody>
</table>

Tables 2-4 show that LINGO performs slightly better than the PSO (less than 1 % difference). It takes less than 10 seconds to reach the solution whereas the PSO spends about 10 minutes per run. Some negative results presented in Tables 2-4 look like the PSO may perform better than LINGO. This occurs since the first priority goal (maximization of profit) may move in the opposite direction to the second priority goal (maximization of revenue). LINGO gives the higher value than that of the PSO for the first goal. This may cause the second priority objective value of LINGO lower than that of the PSO. As a result, a negative percentage deviation is then obtained.

The proposed APP model can still be further extended to represent more realistic and comprehensive practice by taking subcontract, backorder, and overtime on holidays into consideration. Also, integer constraints for some parameters are relaxed. This may affect both LINGO and the PSO to some extent and should be investigated further.

6. CONCLUSIONS

A PSO based goal programming is applied to solve multiple objective APP problems. A final plan of product price, size of workforce, production, and inventory can be determined. The quality of solutions obtained by the PSO clearly shows near-optimal solutions even though they are slightly poorer than those of LINGO. Goal programming approach obviously demonstrates its usefulness in handling multiple goals simultaneously. In addition, the PSO can be modified to handle constrained optimization problem, in this case, by using the penalty function method and heuristics for utilizing special structures of the problem.

The PSO also shows its potential to handle a constrained multiple objective optimization problem and could be applied to other similar problems faced by management. Some similar heuristics may be developed to take advantage of unique characteristics of more comprehensive and realistic models such as multiple production lines, subcontract, and backorder.

REFERENCE


