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A CHANCE CONSTRAINT BASED MULTI-ITEM PRODUCTION PLANNING MODEL USING SIMULATION OPTIMIZATION

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ABSTRACT

We consider a single stage multi-item production-inventory system under stochastic demand. We had previously proposed a production planning model integrating ideas from forecast evolution and inventory theory to plan work releases into a production facility in the face of stochastic demand. However, this model is tractable only if the capacity allocations are exogenous. This paper determines the capacity allocated to each product in each period using a genetic algorithm. Computational experiments reveal that the proposed algorithm outperforms the previous approach in both total cost and service level.

1 INTRODUCTION

The coordination of production and inventories across global supply chains is particularly difficult in capital-intensive industries such as semiconductor manufacturing, where high capital costs require factories to maintain high levels of utilization in order to be profitable. The high number of unit operations required by the complex production processes, together with the high equipment utilization and high levels of variability due to engineering holds, yields excursions and unplanned equipment downtime (Uzsoy et al. 1992, Uzsoy et al. 1994) result in a complex production environment with cycle times of the order of several weeks. Products are sold in several markets with different dynamics and uncertain demand, and both production and distribution networks are global in nature.

The primary objective of supply chain management in this domain is to plan the releases of work into the factories in such a manner that on-time delivery targets are met. The uncertain nature of demand, in turn, requires appropriate levels of safety stocks throughout the supply chain to meet demand at desired service levels. The two sets of decisions are intimately interrelated. Classical inventory theory (Zipkin 2000, Axsater 2010) has shown that the amount of safety stock necessary to achieve a specified service level is determined by the distribution of the total demand over the replenishment lead time. When replenishment orders are placed with a production facility, such as a semiconductor wafer fab, the lead time is determined by the cycle time of the factory. The need to hold safety stocks results in additional orders being placed on production facilities to replenish depleted safety stocks, causing increased resource utilization in the factory, and hence higher cycle times and WIP levels (Hopp and Spearman 2008). These higher cycle times and WIP levels, in turn, alter the distribution of the lead time demand, requiring additional safety stocks. Thus there is potential for a harmful positive feedback loop between safety stock levels and factory cycle times, requiring planning procedures that consider both safety stocks and work releases in an integrated manner.

However, production planning and inventory management have mostly been addressed independently of one another. Most of the literature on production planning (Johnson and Montgomery 1974, Voss and Woodruff 2003) is based on deterministic mathematical programming formulations that do not consider uncertain demand. Stochastic optimization techniques such as stochastic programming (Birge and Louveaux 1997) and simulation optimization (Fu 2002, Zapata et al. 2011) have had limited impact due to their high computational burden. The literature on inventory models (Zipkin 2000, Axsater 2010), on the other hand, focuses on stochastic demand under relatively simple replenishment models. The main finding from this work has been the optimality of base-stock policies for a wide range of problems with linear holding and backordering costs (Clark and Scarf 1960). However, the primary method for exact solutions in this area is stochastic dynamic programming, which is computationally intractable as problem size increases.

The current state of the art suggests that seeking exact solutions to these complex production-inventory problems is unlikely to produce practical solutions. Instead, we explore approximate solutions that combine the ability of mathematical programming models to handle capacity constraints and the robust performance of the base stock policies derived from inventory theory. To this end, we have developed a series of mathematical programming models using chance constraints to develop approximate solutions for single-item single-stage production-inventory systems. However, the presence of capacity constraints renders the development of models for capacitated multi-item systems difficult.

In this paper we extend a multiple-item single stage model developed in previous work (Albey et al. 2015) to a capacitated multi-item system with stochastic demand. Planning takes place in a rolling horizon environment, where demand forecasts are updated and work release decisions implemented at each planning epoch. Exploiting the fact that the linear programming model for this system can be separated into independent single-item models if the capacity allocation among products in each period is specified, we use a simulation optimization approach based on a genetic algorithm to search for near-optimal capacity allocations, using the single-product models as a fitness measure. Computational experiments suggest that the procedure can obtain high-quality solutions in reasonable CPU times.

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 presents the planning framework, the production planning model and the genetic algorithm used to allocate capacity. Section 4 presents the design of the numerical experiments, Section 5 the results, while conclusions and directions for future research are presented in Section 6.

2 PREVIOUS RELATED WORK

Mathematical programming approaches to production planning (Johnson and Montgomery 1974, Saad 1982, Voss and Woodruff 2003, Missbauer and Uzsoy 2011) generally treat all problem parameters, including demand, as deterministic. The implicit assumption is often that these models will be used in a rolling environment (Baker and Peterson 1979), where at each decision epoch (point of time where a set of planning decisions are made) the model is solved for some number of periods, but only decisions for the current period are implemented. Spitter et al. (2005, 2005) report on the performance of linear programming models or supply chain planning in this context.

Production planning problems with stochastic demand have been addressed using stochastic programming (Peters et al. 1977, Higle and Kempf 2011), robust optimization (Bertsimas and Sim 2004, Bertsimas and Thiele 2006), and chance constraints. Stochastic programming rapidly encounters computational difficulties due to the rapid increase in the size of the scenario tree with increasing number of scenarios and decision epochs. Robust optimization appears more promising, but care must be exercised in setting parameters appropriately, which can be difficult in large systems with many products.

Chance constraints (Charnes and Cooper 1959, Prékopa 1995) formulate stochastic optimization problems using constraints that can be violated with a specified probability. Although these formulations can cause theoretical problems due to the fact that the costs of recourse actions taken in the event of constraint violations are not considered (Blau 1974), under fairly mild conditions they lead to tractable linear programming models. Ravindran et al. (2011) propose a chance-constrained model for production planning in a single stage single-item system under stochastic demand and workload-dependent lead times, which is extended by Orcun et al. (2009). Aouam and Uzsoy (2012, 2014) compare the performance of chance constrained models, stochastic programming and robust optimization on a system similar to that considered here, without the rolling horizon component or evolving forecasts. They find that the chance-constrained models provide solutions comparable in quality to those from the other techniques with much simpler formulations. Norouzi (2013) proposes an alternative chance constraint based on the results of Glasserman (1997) for a capacitated single-stage single-item inventory model. Albey et al. (2015) implement this model using data from a major semiconductor manufacturer, incorporating forecast evolution using the Martingale Model of Forecast Evolution (MMFE) proposed by Heath and Jackson (1994), and show that the model has promising performance.

Simulation optimization approaches (Fu 2002, Zapata et al. 2011) have been used in a variety of problem domains, but their high computational burden has limited their application to production planning problems. Planning production in a large facility over a long planning horizon requires many time-consuming simulation runs, as well as a large number of iterations while searching for a local optimum. Liu et al. (2011) compare the performance of a simulation optimization procedure based on a multiobjective genetic algorithm for a scaled-down semiconductor wafer fab (Kayton et al. 1997). Li et al. (2016) implement simulation optimization using a pre-fitted metamodel, avoiding the need for time-consuming simulation replications during the optimization process.

The model presented in this paper is a direct extension of the work of Norouzi (2013) and Albey et al. (2015) to a single-stage multi-item production inventory system. While the system considered is simple compared to practical semiconductor supply chains, the results provide an initial step to the development of more complex models for larger systems. The computational efficiency of the chance-constrained model allows the simulation optimization to identify near-optimal capacity allocations for the different products in modest CPU times. The solutions thus obtained provide a benchmark for other heuristics, and provide insight into the structure of solutions that can be exploited to develop more efficient procedures.

3 PRODUCTION PLANNING FRAMEWORK

3.1 Planning Framework Assumptions

We assume that planning takes place in a rolling horizon framework, where demand forecasts for future periods are updated in each period as the new information becomes available. Eventually, the sequence of forecasts for a future period evolves into its realized demand once the demand is observed. The integration of forecast updates into a production planning model requires a probabilistic model of the evolution of the forecasts over time. For this purpose, we use the additive model of forecast evolution proposed by Heath and Jackson (1994) and extended by Norouzi and Uzsoy (2014) which considers the correlation between forecast updates. This model was successfully integrated into a chance constraint based production planning model (Albey et al. 2015), which forms the basis of the model in this paper. However, our previous model assumed that capacity is allocated among products in proportion to their mean demand. This paper extends this work to obtain a near-optimal capacity allocation as part of the model solution.

We consider a finite horizon periodic review setting for a planning horizon of G periods, in which the planning model seeks decisions for the next $T < G$ periods. We define a decision stage or epoch s to be one of a consecutively numbered set of points in time at which the decision maker updates demand forecasts and determines how much of each product to release into the system (referred to as releases) for the next $T \leq G$ periods. Stage s, spanning the time between stages s and $s+1$, represents the current point in time and stage *s-1* the time in the past when the most recent decisions were made. Demand forecasts are available for some number $H \leq T$ of future periods, referred to as the forecast horizon.

Let $i = 1, \ldots, I$ denote the product index and $t = 1, \ldots, T$ the index for periods. All products i have mean demand of μ_D^i, and require unit processing time. The production system has known capacity C representing the total number of products that can be produced in a planning period. CR_{st}^i represents the capacity allocated to product i at stage s for period t. For a given stage s and product i the demand forecast for period t is denoted by D_{st}^i, the amount on hand at the end of period t by FGI_{st}^i, and the amount backordered at the end of period t by B_{st}^i. Without loss of generality we assume a production lead time of one period such that the amount of material X_{st}^i released in period t can only be used to satisfy demand in period $t+1$. The unit inventory holding cost, unit backorder cost and unit shortfall cost are denoted by c_h^i, c_b^i and c_y^i, respectively.

We assume that the system operates under a base stock policy. When the production capacity is not sufficient to raise the inventory position of product i at the beginning of period t to the specified base stock level BS_t^i, the shortage, referred to as the shortfall (Glasserman 1997), is a random variable

$$Y_{st}^i = max(0, BS_{st}^i - \left(FGI_{t-1}^i - B_{s,t-1}^i + X_{st}^i\right)). \tag{1}$$

The assumption of a base stock policy implies that

$$FGI_{st}^i - B_{st}^i + X_{s,t+1}^i + Y_{s,t+1}^i \geq BS_{s,t+1}^i. \tag{2}$$

i.e., we should release enough material in previous periods to raise the sum of on-hand inventory, $FGI_{st}^i - B_{st}^i + X_{s,t+1}^i$, and possible shortfall, $Y_{s,t+1}^i$, at the start of period $t+1$ to at least $BS_{s,t+1}^i$ units with high probability determined by the desired Type-1 service level, i.e., the average probability of no stockout. The cost-minimizing base stock level ${BS_{st}^i}^*$ is given by:

$${BS_{s,t+1}^i}^* = G_{s,t+1}^{-1}\left(c_b^i/\left(c_h^i + c_b^i\right)\right), \tag{3}$$

where $G_{s,t+1}^{-1}(\alpha)$ represents the α percentile of the variable $D_{s,t+1}^i + Y_{s,t+1}^i$. This result states that the optimal base stock level is a critical fractile. Norouzi (2013) shows that when backorder cost is significantly larger than inventory holding cost, (3) is well approximated by

$${G^{-1}}_{s,t+1}^i\left(c_b^i/\left(c_h^i + c_b^i\right)\right) = \frac{1}{\theta} ln\left(1 + c_b^i/c_h^i\right) - \beta + D_{s,t+1} + \frac{1}{2}\gamma_{s,(t+1,t+1)}\theta, \tag{4}$$

where $\theta = 2(CR_{st}^i - \mu_D^i)/(\gamma_0 + 2\sum_{t=1}^H \gamma_t)$ such that $CR_{st}^i > \mu_D^i$; and the correction term for normally distributed demand is $\beta = 0.583\sqrt{\gamma_0 + 2\sum_{t=1}^H \gamma_t}$ (Toktay and Wein 2001), where γ_t represents the covariance between the demand forecasts for periods t and t+p determined by the covariances of the forecast update vectors used in the MMFE. Details of the integration of the MMFE into (4) are given by Norouzi and Uzsoy (2014) and Albey et al. (2015). These approximations yield a chance-constrained formulation where the right hand side of the chance constraint can be calculated offline. Albey et al.(2015) show that the chance constraint model obtained using this approximation is promising, and that the integration of forecast evolution leads to improved performance over models that do not consider them. Norouzi et al. (2014) show that this formulation can obtain solutions of comparable quality to those obtained using stochastic programming. In the next subsection, the production planning model that integrates the MMFE and chance constraints is presented.

3.2 Chance Constraint Based Production Planning Model: CC Model

The multiproduct chance-constrained model of Albey et al.(2015) that forms the basis of the work in this paper is stated below. For simplicity the *s* index, the stage index in the rolling horizon context, is dropped, with the understanding that the model represents the optimization problem solved at each decision stage *s*.

$$Min\ z = \sum_{i=1}^{I}\sum_{t=1}^{T}\left(c_h^i FGI_t^i + c_b^i B_t^i + c_y^i Y_t^i\right) \tag{5}$$

subject to

$$FGI_t^i - B_t^i = FGI_{t-1}^i - B_{t-1}^i + X_t^i - D_t^i \qquad \forall i,\ t=s,\dots,s+H-1 \tag{6}$$

$$X_t^i \le CR_t^i \qquad \forall i,\ t=s,\dots,s+H-1 \tag{7}$$

$$\sum_i CR_t^i \le C_t \qquad \forall t=s,\dots,s+H-1 \tag{8}$$

$$FGI_t^i - B_t^i + X_{t+1}^i + Y_{t+1}^i \ge {G^{-1}}_{t+1}^i\left(c_b^i/\left(c_h^i + c_b^i\right)\right) \qquad \forall i,\ t=s,\dots,s+H-2 \tag{9}$$

$$X_t^i, FGI_t^i, B_t^i, Y_t^i, CR_t^i \ge 0 \qquad \forall i,\ t=s,\dots,s+H-1 \tag{10}$$

The objective function (5) aims to minimize the total backorder, inventory holding and shortfall cost. The shortfall cost is required to ensure that the model obtains meaningful solutions, as discussed in Albey et al. (2015). Constraint set (6) is the demand balance constraint, written for all products and each period in the forecast horizon. Constraint set (7) ensures that production of a product in a period does not exceed its allocated capacity in that period, and constraint set (8) that the total capacity allocated to all products does exceed the available capacity in the period. Constraint (9) is the chance constraint ensuring a service level corresponding to the critical fractile (3), combining (2), (3) and (4) as in Albey et al. (2015). Treating the capacity allocations CR_t^i as decision variables yields a nonlinear, nonconvex optimization model. However, if the CR_t^i are given, the model yields a straightforward linear program. Hence we propose a genetic algorithm to determine the capacity allocations CR_t^i.

3.3 Genetic Algorithm: GA

The proposed GA encodes a population of capacity allocations for each product *i* and each period as a two dimensional matrix $A(s,i) \in (0,1)\ \forall i, s = 1,2,\dots,G$. Each entry a_{si} of $A(s,i)$ lies in the interval (0,1) and represents the fraction of the available capacity in excess of that necessary to meet the mean demands allocated to product *i* in period *s*. To ensure feasibility the capacity allocations for all products in each epoch for all periods add up to 1, i.e. $\sum_i A(s,i) = 1\ \forall s$. The allocation is computed based on excess capacity, because the parameter θ in (4) is constructed assuming that the capacity allocated to each product is strictly greater than the mean demand of that product. In other words, in each period a fixed portion of the capacity, enough to produce mean demand for each product is allocated to products, while any remaining capacity is allocated to products using the $A(s,i)$ values. Hence for each instance of the CC model the CR_{st}^i values are generated as:

$$CR_{st}^i = \mu_D^i + A(t,i)C_t\ \ \forall i, t = s, s+1, \dots, s+H-1 \tag{11}$$

The fitness value of each valid encoding is obtained by solving the CC model (5)-(10) in a rolling horizon setting under a set of simulated demand realizations, as shown in Figure 1.

The GA algorithm is executed as follows: the first individual in the initial population is generated using the normalized mean demand values, given by $A(s,i) = \mu_D^i / \sum_i \mu_D^i\ \ \forall i, s = 1,2,\dots,G$, which constitutes the benchmark allocation rule. For the remaining individuals, the $A(s,i)$ matrix is created randomly and the entries are normalized such that $\sum_i A(s,i) = 1 \ \forall s,i$ to ensure capacity feasibility of the solutions. The pseudocode of the overall GA framework is presented in Table 1.

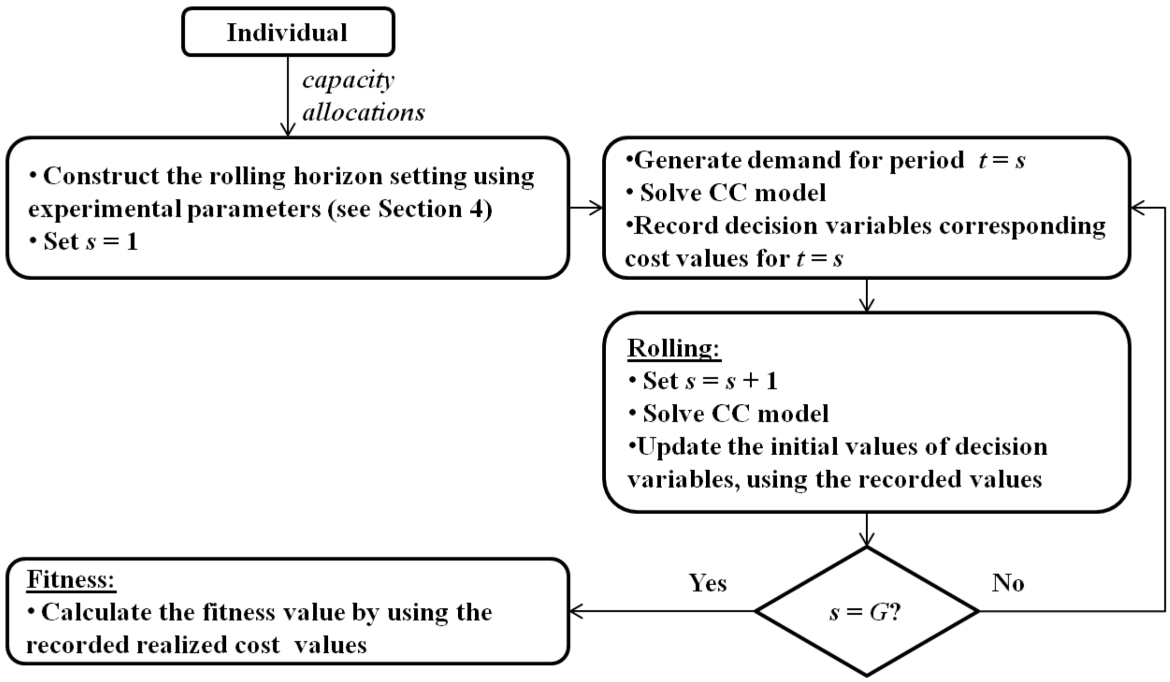

Figure 1: Fitness calculation.

Table 1: Pseudocode of the GA.

1-Generate an initial generation of size *N* (one individual using mean demands, *N-1* individuals randomly)
2-Repeat until L generations have been generated or no improvement in the best solution has been found in γ consecutive generations:
2.1-Immigration: Select the fittest *p%* of individuals from the most recent generation and transfer them into the new generation.
2.2- Repeat for each member of the population:
2.2.1-Parent Selection: An individual, i.e. parent candidate, PC_1, is randomly generated and a random individual, PC_2, is selected from the current population. First parent is set as the fittest of PC_1 and PC_2. This selection is called “selective random”.
2.2.2-Crossover: Generate a random number uniformly distributed between 0 and 1. If the number is less than the crossover probability P_c apply crossover by selecting the mate using the roulette wheel method (Goldberg 1989).
2.2.3-Mutation: Generate a random number uniformly distributed between 0 and 1. If the number is less than the mutation probability P_m implement mutation.
2.2.4-Insertion: Using the procedure described in Figure 1 calculate the fitness of the individual obtained after possible crossover and mutation operations and add the individual to the current population.
3- Report the individual with the highest fitness value in the final population.

The crossover step is executed in a manner similar to uniform crossover (Goldberg 1989) with a minor modification. The smallest meaningful part of the solution encoding is assumed to be the allocation ratio in a period. During offspring creation, a decision is made for each period t as to which parent’s capacity allocation information will be transferred to the offspring. The probability of each parent being selected is biased towards the fitter of the parents in proportion to the relative magnitudes of their fitness values. This crossover process generates the gene of the offspring period by period and guarantees capacity feasibility.

The mutation process is executed after crossover. If the individual has gone through a crossover and its new fitness value is better than the best solution found to date, the mutation process is skipped. Otherwise, mutation is executed with mutation probability, P_m. The mutation process reviews every entry in $A(s,i)$ and decides whether or not to mutate the entry based on a mutation threshold probability P_{mt}. For each entry of $A(s,i)$, a U(0,1) random number is generated and compared to P_{mt}. At the end of the mutation process, a normalization step is executed such that $\sum_i A(s,i) = 1 \;\; \forall s,i$ is retained. The values of the GA parameters were selected through a preliminary experiment and are listed in Table 2.

Table 2: Selected values for GA parameters.

GA Parameters	Selected Values
$N, L, \gamma, p\%, P_c, P_m, P_{mt}$	200,2000,5,10%, 0.80,0.05, 0.15

4 EXPERIMENTAL DESIGN

The experiments are designed to cover six months of rolling planning implementation with weekly planning stages. The planning model covers a four week period. Thus we set G = 26, T = 4 and H = 3, all in units of weeks. The forecast horizon is H = 3 weeks because the current period does not require a demand update, since demand is realized at the beginning of the period.

We compare the performance of the proposed approach to the mean demand allocation rule used in our previous work, under which capacity in each period is allocated to the products based on their mean demand values. The planning model using the capacity allocation values generated with this rule will be referred to as the MA model. The performance of the GA model is compared to that of MA using 16 different test instances. The values of *G, T* and *H* remain fixed in all these instances. Note that no GA is used with the MA model, under which the demand for the current period is realized and forecasts for future periods updated at each decision stage. The finished goods inventory (FGI) holding and backorder costs along with the realized service level over the entire planning horizon of *G* periods are computed to obtain the final realized cost of the production plan found by the models. At each planning epoch *s*, the demand for the current planning period (that is the planning period *t*, where *t* = *s*) is realized and corresponding FGI, backorder and shortfall levels and associated cost values are computed using the output of the mathematical model.

16 test instances are generated. The base scenario has three products whose demands follow normal distributions with the parameters listed in Table 3. Different versions of the base scenario are generated with different cost, service level and capacity settings. To demonstrate the scalability of the proposed approach, a nine product scenario is also included in the experimental analysis.

Table 3: Demand Parameters.

	Mean Demand	Coefficient of Variation
Product 1	125	0.20
Product 2	250	0.30
Product 3	50	0.20

We conduct three different experiments. In the first, Scenarios 1-12, it is assumed that the cost structure and the capacity usage of all products are identical, and vary the available capacity and the target service levels. We consider three target service level values (0.90, 0.94, 0.98). The capacity level is represented as a multiple of the total mean demand over all products, so that a capacity level of 1.10 indicates that the available capacity is 10% higher than the total mean demand. Four different capacity levels are used (1.30, 1.20, 1.10, 1.05). For a fixed FGI holding cost and a given service level, the backorder cost is computed using the newsvendor equation. The shortfall cost is set equal to the half of the back order cost, which was found to yield the best performance (Albey et al. 2015). Initial FGI, backorder and shortfall levels are assumed zero. Variance covariance matrices (VCV) for the forecast updates are generated randomly, and forecast updates are generated using multivariate normal distributions as discussed in Albey et al ((2015).

5 RESULTS

The realized total cost values of the GA and MA models for Scenarios1-12 are presented in Figure 2. For all instances the realized cost of the GA approach is less than that of MA approach. It should also be noted that the realized backorder costs of GA never exceed those of MA, indicating that GA yields better production plans in terms of the achieved service levels. These results indicate that GA approach does a better job of utilizing the chance constraints and produces plans with low cost and high service level.

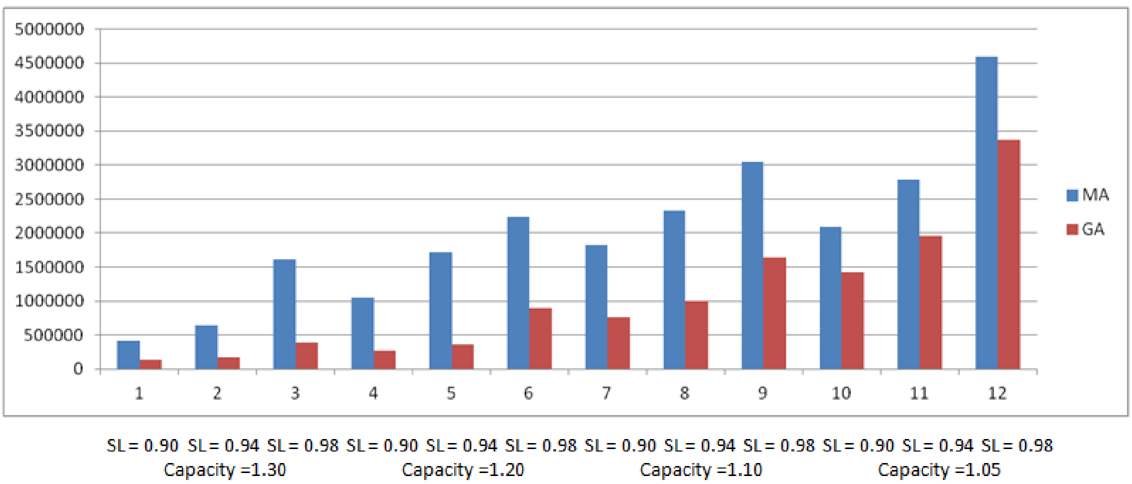

Figure 2: Total cost comparison of CC and MA model under varying capacity and service level settings.

In the second set of experiments, three scenarios (Scenarios13-15) are generated using a service level of 0.94 and capacity level of 1.10. In Scenario 13, the FGI costs of the products (and hence their backorder costs, due to the use of the newsvendor equation) are generated in proportion to their mean demands, i.e. product with a higher mean demand assigned a higher FGI holding cost; whereas in Scenario 14, the FGI holding costs are inversely proportional to the mean demand values. In Scenario 15, the VCV matrices of the products are changed such that the magnitudes of the off-diagonal entries are increased. In all Scenarios 13-15, the production system has initial FGI levels equal to the mean demand of the products. As seen in Figure 3, the GA model yields substantially better results than the MA model in Scenario 13, where the high backorder costs for high-demand products results in higher backorder costs. The increased variability in demand in Scenario 15 results in a smaller difference between the two models in terms of magnitude of total cost, but the percentage difference is still substantial, as seen in Table 4.

The final experimental setting, Scenario 15 with nine products, is used to test the scalability of the proposed approach with capacity factor 1.10 and target SL of 0.94. Initial FGI values are set equal to half the mean demand values, together with the VCV matrices and cost structures in Scenarios 1-15. A detailed breakdown of the costs and achieved service levels for each product are presented in Table 4. The last row of Table 4 presents the average service level and total cost over all products. The GA approach finds a production plan with 37% less total cost than that of MA, and is far more effective in meeting the desired service level (99% compared to 82%).

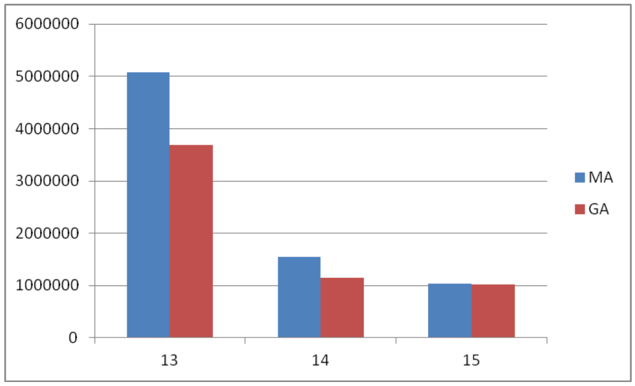

Figure 3: Comparison of total cost of MA and GA for Scenarios13-15.

Table 4: Model Results for Scenario15.

MA Model						GA Model				
Product	SL	FGI Cost	BO Cost	Total Cost		Product	SL	FGI Cost	BO Cost	Total Cost
1	0.65	87,804	746,043	833,847		1	1.00	251,881	0	251,881
2	0.69	305,230	2,666,710	2,971,939		2	1.00	955,579	0	955,579
3	0.62	16,453	568,627	585,080		3	1.00	64,296	0	64,296
4	1.00	1,212,119	0	1,212,119		4	1.00	1,567,416	0	1,567,416
5	1.00	3,596,226	0	3,596,226		5	1.00	2,278,212	0	2,278,212
6	0.69	38,035	415,480	453,515		6	0.92	88,982	46707	135,689
7	1.00	740,619	0	740,619		7	1.00	1,074,268	0	1,074,268
8	0.69	267,520	1,067,620	1,335,140		8	1.00	1,084,150	0	1,084,150
9	1.00	341,036	0	341,036		9	1.00	221,948	0	221,948
Total		**660,5041**	**5,464,480**	**12,069,521**				**7,586,731**	**46707**	**7,633,438**

The experiments were conducted on a Windows 7 PC with an 8 core (2.93 GHz) Intel i7 Processor and 8 GB of RAM. Algorithms are implemented in C#, and we use the IBM ILOG CPLEX 12 Callable Library (ILOG 2007) to solve the mathematical models. The GA runs, on the average, requires 7.5 seconds for a single generation of 200 individuals, which represents a considerable CPU time. However, the vastly improved quality of the solutions suggests that this approach is well worth pursuing.

6 CONCLUSIONS AND FUTURE RESEARCH

This paper extends a previously developed chance constrained production planning model with forecast evolution and stochastic demand to a multiproduct environment using a genetic algorithm to search for the cost-minimizing capacity allocations among products. The results indicate that the proposed model is capable of obtaining significantly improved solutions over a baseline method that allocates capacity in proportion to mean demands. Given the well-known difficulty of obtaining effective allocation rules in multiproduct capacitated inventory systems, these results are promising. The primary drawback of this approach is its potentially high computation time, which must be addressed for it to be useful in industrial environments with multiple products. Opportunities for improved efficiency may lie in improved tuning of the GA parameters to avoid unnecessary iterations, and better implementation.

Several additional directions for future research are apparent. The extension of this type of model to multiechelon production-inventory systems with a serial structure has been suggested by Ravindran et al. (2011), and appears quite feasible. Extension to more general network structures such as distribution networks remains challenging. Finally, the development of exact solution procedures such as stochastic programming models is required in order to determine how close to optimality the solutions obtained actually are.

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