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MULTI-OBJECTIVE OPTIMIZATION FOR THE SUCCESSIVE MANUFACTURING PROCESSES OF THE PAPER SUPPLY CHAIN

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ABSTRACT

The traditional production focus in the paper industry has been on maximizing machine utilization and minimization of cost but it has had adverse effects on the overall supply chain benchmarks such as over capacity, long lead times, excessive inventory and low customer service. A least cost production plan for the paper manufacturing and conversion stages results in poor cycle service levels where many of the customer orders may fail to meet the due dates. Conversely, a service level maximization approach yields a poor solution with respect to production costs. Therefore, production planning problem in the paper supply chain is faced with more than one optimization criterion which transforms the traditional cost minimization objective into a multiple objective optimization problem with consideration for meeting customer requirements for different grades and the due dates. In this paper, a multi-objective optimization approach to the successive production processes of paper manufacturing and conversion is advocated and applied to obtain a range of compromise solutions between the two conflicting objectives of production cost minimization and maximization of the cycle service levels.

KEYWORDS

Production planning in paper industry, Multi-objective optimization, Genetic Algorithms

1. INTRODUCTION

The traditional production focus in the paper industry has been on economies of scale for cost advantage but it has had adverse effects on the overall supply chain benchmarks such as over capacity, long lead times, excessive inventory and low customer service (Ranta, Ollus & Leppänen 1992; Hameri & Holmström 1997; Hameri & Lehtonen 2001; De Treville, Shapiro & Hameri 2004). This led to a gradual shift to a more flexible production strategy with shorter production cycle times and increased number of grade changeovers for better customer service. While the capacity driven strategy may still be valid for few standardized products with high volume, the increased product customization in the pulp and paper supply chain warrants a focus on meeting customer requirements that is only possible through a flexible production approach.

Hameri & Lehtonen (2001) described a transition in the production strategy for five Nordic paper mills manufacturing paperboard, specialty, and standard fine paper. The volume driven strategy with emphasis on maximum utilization and low cost was replaced by a flexible approach that focused on small lot sizes, shorter lead times and punctual deliveries. Small lot sizes essentially means a higher frequency of grade changeovers which improves the customer service but additional costs are incurred because of increased number of production setups. Different paper grades require a common production resource and whenever a production switch to a new grade is made, production time is lost in setting up the machinery. In the paper industry, setup costs are more important as the machine keeps making paper but it takes time to adjust to the quality settings of the new grade. The paper produced in the transition time is rejected. Therefore, apart from the opportunity costs (i.e. lost production time), significant material losses are also encountered.

Another aspect of sharing resources is that the production of different grades cannot happen at the same time, therefore, customer orders must be sequenced which has repercussions for the cycle service levels. Apart from the order sequencing issue and its effects on cycle service levels, inventory holding costs are also an important consideration for planning purposes, Grade changeovers can be minimized for particular production plan by scheduling each grade only once during the planning horizon till the demand is met, however, the opportunity costs of capital tied up in inventory, the direct costs of storing goods and holding items also prohibit large stacks of inventory. Furthermore, in some instances, securing additional capital may also be a concern and therefore, another reason to limit inventory holding costs.

2. FROM SINGLE OBJECTIVE TO MULTI-OBJECTIVE OPTIMIZATION

The conventional single objective optimization literature identifies the production planning at the paper machine as 'a lot-sizing problem' which finds a balance between low setup costs (favouring large production lots) and low holding costs (favouring a lot-for-lot-like production where sequence decisions have to be made due to sharing common resources) (Rizk & Martel 2001). An aggregated cost function representing grade changeover cost, inventory holding cost and tardiness penalty is minimized to obtain a single best solution. A least cost production plan for the paper manufacturing and conversion stages results in poor cycle service levels where many of the customer orders fail to meet due dates.

In most real world situations, a decision maker may not opt for least cost solution because not all customer requirements are met. Conversely, a production plan that endeavours to meet all customer orders might be too expensive because of too many grade changeovers. In such scenarios, a single objective optimization approach which either minimizes the production cost or maximizes the customer service fails to capture the dynamics of the decision environment. Instead, the decision maker is more likely to be interested in solutions that give a range of values in between the two extremes obtained by the multi-objective optimization. Service level maximization and minimization of production cost are conflicting objectives in the pulp and paper supply chain. A single optimization criterion of either cost minimization or maximization of service levels yields a good solution from one perspective but is likely to give poor results for the corresponding conflicting objective. Therefore, production planning problem in the pulp and paper supply chain is faced with more than one optimization criterion which transforms the traditional cost minimization objective into a multiple objective optimization problem with consideration for meeting customer requirements for different grades and the due dates.

Whenever an optimization problem is faced with multiple and conflicting objectives, the usual meaning of the optimum does not suffice in the decision making context because a solution optimizing all objectives simultaneously generally does not exist. The identification of a best solution requires a trade-off or compromise between the conflicting objectives. The tradeoff between conflicting objectives has been most effectively captured with the help of a widely known economic concept of Pareto optimality or dominance wherein solutions are sought from which it is impossible to improve one objective without deterioration in another objective. The multi-objective optimization approach utilizes the Pareto dominance concept to tackle conflicting objectives and is different to the conventional single objective optimization approach on the following counts:

- There are at least two distinct objectives instead of one.
- It results in multiple solutions giving a range of values between the extreme possibilities for each objective.
- It possesses two different search spaces: objective space and decision space.
- The search process is not influenced by the magnitude of the cost coefficients associated with each objective.

The usefulness of a multi-objective optimization approach is accentuated in the situations where it is hard to estimate the cost coefficients associated with the objectives because the search process is unaffected by their magnitude. Even if these coefficients are estimated, their magnitude represents a bias that guides the search process in a specific direction. A multi-objective optimization approach removes the bias towards a particular objective by either normalizing the coefficients of the aggregated objective function, using only one objective at a time or by incorporating the Pareto rank or dominance based approach where all objectives are given equal importance during the pair-wise comparison for dominance.

Traditionally, most optimization problems have been solved through a single objective approach, however, over the years a parallel line of research has evolved by taking a new perspective on the combinatorial optimization problems hitherto treated as single objective problems. For example, vehicle routing, travelling salesman, timetabling, machine scheduling, airline crew scheduling problems and cutting stock problems have long been optimized using single objectives but there is a growing realization in the research community that most real world problems need to satisfy more than one criterion for optimization. Routing problems such as travelling salesman and vehicle routing are generally optimized by minimizing the total travelled distance but Ombuki, Ross & Hanshar (2006) identified minimization of the number of vehicles used as another objective and argued that vehicle routing is intrinsically a multi objective optimization problem. Jozefowiez, Semet & Talbi (2008) carried out a survey of multi objective optimization methods applied to routing problems and noted that depending upon the problem context, the optimization considerations included minimization of criteria like travelled distance, vehicles, vehicle waiting times, merchandize deterioration, mean transit time, variance in transit time, individual perceived risk, the actual risk, individual disutility, unused working hours, the length of the longest tour whereas route balancing, maximization of capacity utilization and size of the population covered was used. Similarly, for time tabling problems, Datta, Deb & Fonseca (2007) proposed two conflicting minimization objectives of average number of weekly free time slots between two classes for the students and average number of weekly consecutive classes for the teachers. For machine scheduling, Li et al. (2010) used minimization of make span, completion time and tardiness as optimization criteria. For crew scheduling, total cost, delays, and unbalanced utilization have been simultaneously minimized (Lucic & Teodorovic 2007). Ghoseiri, Szidarovszky & Asgharpour (2004) used a dual objective scheduling approach for train operations by considering lower fuel cost for the railway company as one objective while shortening total passenger-time is the other objective.

In this paper, a multi-objective optimization approach to the successive manufacturing processes of lot-sizing and cutting stock problem is advocated to obtain a range of compromise solutions between the two conflicting objectives of production cost minimization and maximizing the cycle service levels. In the next section, the production context is defined and a bi-objective formulation is developed for simultaneously minimizing the production cost and maximization of cycle service levels. Solution methods are described in section 4 and experimental results are discussed in section 5. The discussion on results is carried out in section 6. The paper is concluded in section 7.

3. MODEL FORMULATION

3.1 PROBLEM DEFINITION

The planning problem is essentially to determine the production levels of multiple finished products (FP) and intermediate products (IP) over a finite planning horizon in a paper mill, where paper production and conversion are two successive stages. Large reels of paper called Jumbos are produced on paper machines which are cut into smaller rolls as per customer's specifications during the conversion process. A schematic of the two processes is shown in figure 1:

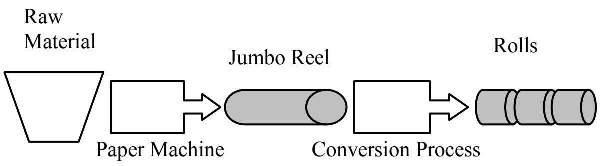

Figure 1: A Schematic of Paper Manufacturing Process

The customer orders for the finished products have the following characteristics:

- Paper grade
- Roll's width
- Number of rolls required
- Order due dates which can be a particular day of the week long planning horizon. It is assumed that in case, the roll requires further finishing activities, the quoted due date includes necessary time buffer.

It is assumed that the cutting stage is unconstrained because the rate of cutting jumbo reels is much faster than the production rate at the paper machine. It is a reasonable assumption because the paper machine is usually the bottleneck resource in the pulp and paper supply chain (Martel et al. 2005).The FP demand over the entire planning horizon has to be met; however, if an order cannot be delivered in time, it incurs a tardiness cost 'M'. Cycle Service Level (CSL) is defined as the probability that the cycle time for the customer's order will be less than the quoted lead time (Hopp & Spearman 2008). Mathematically

$$\text{CSL} = \text{Probability } \{\text{Cycle Time} \leq \text{Lead Time}\}$$

The demand of intermediate products i.e jumbo reels is unknown but derived through the independent demand i.e FP demand. No inventory of Jumbo reels is kept; however, finished products can be stored at the manufacturing facility. Changeover costs are incurred whenever a different grade of paper is manufactured on a paper machine.

3.2 MATHEMATICAL FORMULATION

In this section, a two step procedure is used for simultaneous minimization of production cost and maximization of cycle service levels. The major components of paper production cost are trim loss and grade changeover cost. While minimization of trim loss is the only criterion for the paper conversion process, a tradeoff curve between the two conflicting aims of grade changeover cost minimization and improved cycle service levels is obtained by employing a bi-objective formulation in the following manner:

Step 1. The conversion process is solved with a single objective of minimization of trim loss.

Step 2. Allocation of cutting patterns to different planning periods triggering the production of jumbo reels of the respective grades with a bi objective optimization criterion namely, grade changeover cost minimization and service level maximization. Mathematically,

Objective to be minimized

$$f_1 = \sum_{t}^{T} \sum_{i \in IP} K_{it} \rho_{it} \tag{1}$$

$$f_2 = \sum_{t}^{T} \sum_{i' \in FP} y_{i't} \tag{2}$$

$$C_t \geq a_{it} Q_{it} + k_{it} \rho_{it} \tag{3}$$

$$d_{i't} = Q_{i't} + I_{i'(t-1)} - I_{i't} \tag{4}$$

$$\sum_{t}^{T} Q_{it} - \sum_{j \in J} x_{ij} = 0 \tag{5}$$

$$\rho \in (0,1) \tag{6}$$

$$Q_{it}, Q_{i't} \geq 0, Integer \tag{7}$$

The indexes, parameters, sets and decision variables used in the above formulation are explained in table 1. The planning problem has been formulated as a bi-objective minimization problem with f_1 representing the grade changeover costs (1); and service level improvements have been indirectly formulated in f_2 as minimization of late orders $y_{i't}$ (2). Customer orders for the finished product *i'* that will not be delivered by the customer specified due date are to be minimized along with the grade changeover costs incurred on the paper machine subject to the capacity constraint (3) and the material balancing constraints (4) and (5). While the constraint (4) ensures that the end demand of finished products is met, constraint (5) stipulates that the cut finished products are equal to the number of jumbo reels of a particular grade (IP), not allowing any inventory of the intermediate products. Constraints (6) and (7) ensure integer solution to the planning problem.

Table 1: Notations

T	=	Length of the planning Horizon
t	=	A single planning period
i	ϵ	Intermediate Products *(IP)*
i'	ϵ	Finished Products *(FP)*
j	ϵ	A cutting pattern
x_{ij}	=	Number of times the *jth* pattern is used on *IP i* to generate *FP i'*
$d_{i't}$	=	Demand for the FP *i'* in period
C_t	=	Paper machine's production capacity (hours)
k_{it}	=	Grade changeover time for IP *i* (hours)
K_{it}	=	Grade changeover cost for IP *i* (hours)
a_{it}	=	Capacity consumption rate of IP *i* (hours/metric ton)
$Q_{i't}$	=	Quantity of FP *i'* produced during period *t*
ρ_{it}	=	Setup Indicator for *IP i* in period *t*
$y_{i't}$	=	FP quantity *i'* that are not delivered within due date
Q_{it}	=	Quantity of *IP i* produced during period *t*
$I_{i't}$	=	Inventory of *FP i'* at the end of period *t*

4. SOLUTION APPROACH

There have been various ways to applying multi-objective optimization approaches but the scaler and Pareto approaches are the main ones. Due to the fundamental difference between the methods employed to approximate the Pareto frontier, these two approaches may differ substantially with each other with regard to suitability for application to a specific decision context and the results obtained. Therefore, it is deemed prudent to test both solution approaches for the production problem of the two successive stages of paper manufacturing. Epsilon constraint method is selected as the scaler approach whereas the non-dominated sorting algorithm-II (NSGA-II) is chosen as the preferred Pareto or multi-objective evolutionary algorithm (MOEA).

4.1 EPSILON CONSTRAINT METHOD WITH STANDARD GA

The epsilon constraint method is a multi-objective optimization converted to a single objective problem and solved through conventional algorithms. Different resolution algorithms ranging from exact to meta-heuristics, depending upon the problem context, have been used in conjunction with epsilon constraint method. A steady state genetic algorithm is used as the resolution algorithm for the bi-objective epsilon constraint formulations (Palisade 2009a). The experimental settings for the GA parameters were as follows:

A uniform crossover value of 0.5 is used across all experiments and auto mutation is used. The latter allows the genetic algorithm to increase the mutation rate automatically when an organism "ages" significantly; that is, it has remained in place over an extended number of trials. For many models, especially where the optimal mutation rate is not known, selecting Auto can give better results faster (Palisade 2009b). Experiments with initial populations of 50, 200, 500 and 1000 have been performed and it was noted that the convergence pattern improved with 500 population size but no improvements were recorded with a 1000 size despite considerable increase in computational workload. Therefore, the population size of 500 was chosen. Similarly, experiments showed that GAs converged before 200 GA equivalent generations or 100,000 iterations; therefore, it was selected as the stopping criterion for all the experiments.

4.2 NON DOMINATED SORTING GENETIC ALGORITHM (NSGA-II)

Multi Objective Evolutionary Algorithms (MOEA) utilize the Pareto based dominance concept in finding out a set of non-dominated solutions. Non Dominated Sorted Genetic Algorithm (NSGA-II) utilizes a non-dominated sorting mechanism to rank the entire population of solutions. Srinivas & Deb (1994) developed NSGA which was the first implementation of a non-dominated sorting mechanism. Later on, NSGA-II was introduced to improve upon the three known deficiencies of NSGA i.e high computational complexity of non-domination sorting, lack of elitism and the use of a user specified sharing parameter for ensuring diversity of solutions to inhibit early convergence (Deb et al. 2002).

The non-domination sorting algorithms rank the whole population of solutions according to the domination count n_i i.e number of solutions that dominate solution i. The best Pareto front will correspond to $n_i = 0$ and it for each of these solutions, a set of solutions S_i being dominated by i is also calculated. S_i is used to find out all the other non-dominated fronts by increasing the domination count by one. The process continues till the whole population is ranked.

NSGA-II was selected as the Pareto based multi objective evolutionary algorithm. GANetXL, is a software platform that utilizes NSGA-II for multi-objective optimization, has been used. It is written in C++ and exploits a component object model (COM) interface to interact with Excel (Savic, Bicik & Morley 2011). Its interface with Excel facilitated the model development with the help of Visual Basic for Application (VBA) macros.

4.3 TEST DATA

The paper machine's speed determining its capacity was provided by an Australian manufacturer along with the grade changeover times. Trade journals were consulted for cost data of different grades of paper kraft. Now, only the details of customer orders for the finished products were unknown and randomly generated data was used to represent these unavailable parameters. The random generation of test data was inspired by Gau & Wascher (1995) but it was modified considerably for the study. The details are as follows:

The customer orders are usually for cut rolls or sheets obtained during conversion stage of a paper mill and are characterized by paper grades, roll's width or sheet's dimensions, number of rolls required and order's due date. Cut roll widths 'l_i' were randomly generated from a uniform distribution so that the simulated widths 'l_i' represent all values from 20% to 80% of jumbo reels length. In the production environment considered, the number of cut rolls required is determined by machine capacity because it is the bottle neck resource in paper manufacturing supply chain. Its capacity is determined by the machine speed which in turns determines the quantity of customer orders it can handle in one week. Also, the randomly generated roll widths affect the required number of jumbo reels because of different combinations of cutting patterns. These two parameters restrict the required quantity; therefore, the number of rolls required is spread across all roll widths to match the paper machine capacity. The order due dates were also randomly generated from a uniform distribution of the five working days in a week long planning horizon which was considered enough to make the point regarding service level considerations.

5. RESULTS

5.1 EPSILON CONSTRAINT METHOD WITH STANDARD GA

In a two step process, the first step involves cutting jumbo reels with a minimum trim loss criterion and the second step allocates the cutting patterns to different planning periods triggering the production of jumbo reels of the respective grades with two minimization objectives namely grade changeover These two vectors determined the extreme values of the Pareto frontier and with ten epsilon increments, the Pareto frontier was approximated in figure 2. A well spread Pareto frontier is obtained between the Nadir and Ideal vectors represented in figure 2 by the light and dark shaded circles respectively.

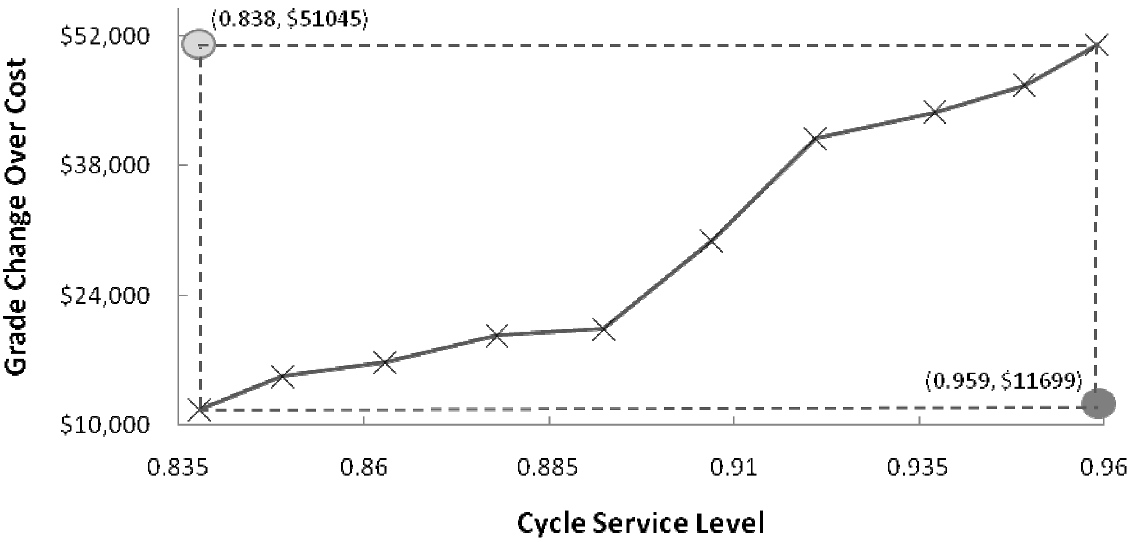

Figure 2: Approximated Pareto Frontier – Epsilon Constraint Method

The Pareto frontier gives the decision maker a range of solutions to choose from. A least cost solution of $11,699 for grade change over costs results in a cycle service level of 0.838 but as the grade changeover cost increased, the service levels also improved. This is because the solutions resulting in lower grade changeover cost correspond to at most one setup in one planning period with the possibility of carrying over the setup state to the next planning period. For example, the solution resulting in grade changeover cost of $11,699 and a cycle service level of 0.838 had only 5 setups in the week long planning horizon. The number of setups in the entire planning horizon gradually increased to 8, 9, 12, 17, 18, 19, 21and so did the corresponding cycle service levels. The maximum cycle service level of 0.959 only resulted because of 21 setups in one week's production schedule but also incurred much higher costs of $51,045.

The important consideration here is whether the estimated Pareto frontier is global or local, i.e can the solutions be improved further? The answer to this question lies in the resolution algorithm. If an exact algorithm was used as the solution approach, the estimated Pareto frontier would have been global and could not have been improved any further. Genetic algorithm was used as the solution approach and being a stochastic search algorithm, the optimality of the obtained solutions can not be guaranteed in a single run. Repeated genetic algorithm runs enhance the probability of obtaining close to optimal solutions (Yuen, Fong & Lam 2001). However, it would have been computationally prohibitive in this case because each of the ten solutions obtained would have to be re-run a number of times. Nevertheless, determining the solution quality is important and another measure for the same could be to solve the same problem by a multi-objective evolutionary algorithm such as NSGA-II and to compare the results.

5.2 NON DOMINATED SORTING GA (NSGA-II)

The state of the art Non Dominated Sorting Genetic Algorithm NSGA II was also applied to the same problem. The initial population was generated randomly. However, it was noted that no individual among the initial population was a feasible solution. The algorithm was allowed to run for 5000 generation with a 500 population. After nearly 50 hours of run time, the algorithm was unable to generate a single feasible solution. Different GA parameters were tried but the generated solutions were always infeasible. The possibility of obtaining feasible solutions after 5000 generations cannot be ruled out but the computational cost was prohibitive. The other alternative is to start with a population of feasible solutions; this approach has been reported in the literature for similar hard combinatorial problems.

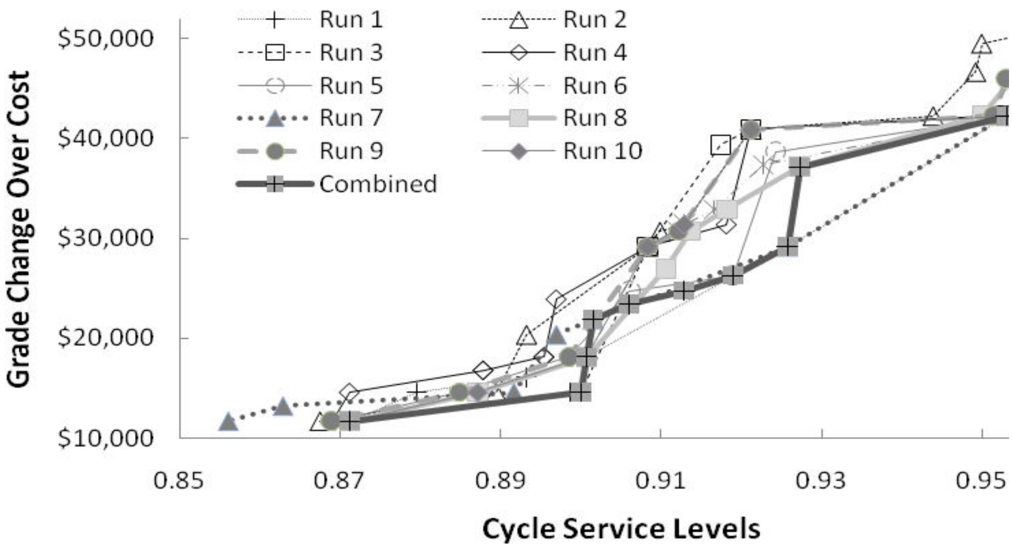

Figure 3: Approximated Pareto Frontier – Multiple NGSA-II Runs

Datta, Deb & Fonseca (2007) also encountered infeasibility of NSGA II generated solutions for a highly constrained university timetabling problem and when they used feasible solutions as the initial population, considerable improvement was recorded. Similarly, Fangguo & Huan (2008) ensured feasibility of all solutions for their dominance based multi-objective genetic algorithm by using an initial feasible population. Sathe, Schenk & Burkhart (2009) employed a clustering algorithm along with NSGA II in order to always generate feasible solutions for a multi-constraint bin packing problem. Li & Hamzaoui (2009) also used initial feasible solutions for their NSGA II implementation. Varela et al.(2009) improved the heuristic solution obtained for a variant of the cutting-stock problem by using it as the initial population for their multi-objective genetic algorithm. Craig, While & Barone (2009) improved the hockey league scheduling with the help of multi-objective evolutionary algorithm by using previous years schedules as the initial population. Reiter & Gutjahr (2010) implemented NSGA-II for a bi-objective vehicle routing problem by using a separate algorithm to generate feasible solutions to be used as an initial population.

The same approach of injecting feasible solutions, including the results obtained by the epsilon constraint method, in the randomized population was used to solve the problem. However, only 30% of the initial population was filled with the feasible solutions while the rest of the population comprised the randomly generated infeasible solutions. This was done to ensure diversity among solutions. Different GA parameter settings were tested and the algorithm did return improved feasible results this time.Details are as follow:

Earlier, in order to generate feasible solutions from the initial random population, a population size of 500 was used which resulted in high computational cost, fifty hours being required for a 5000 generations run. This was because of the computational complexity of NSGA II which is exponentially related to the population size i.e O(MN2) where M is the number of objectives and N is the population size. With feasible solutions as the initial population, the computational load can be reduced by resorting to smaller populations especially because multiple runs are essential to ensure that quality solutions are obtained by stochastic optimizers such as GA. Initially, a population size of 100 was chosen with simple crossover probability of 0.95 and a mutation by gene probability of 0.05. The adaptive mutation probability of 0.01 was also resorted to after 1000 generations. After a four hour run and 2000 generations, there were nine improved feasible solutions and all the rest were copies. Thus, 2000 generations was selected as the stopping criterion. With the same initial feasible solutions and the same proportion of randomized initial infeasible solutions, the algorithm was run ten times.

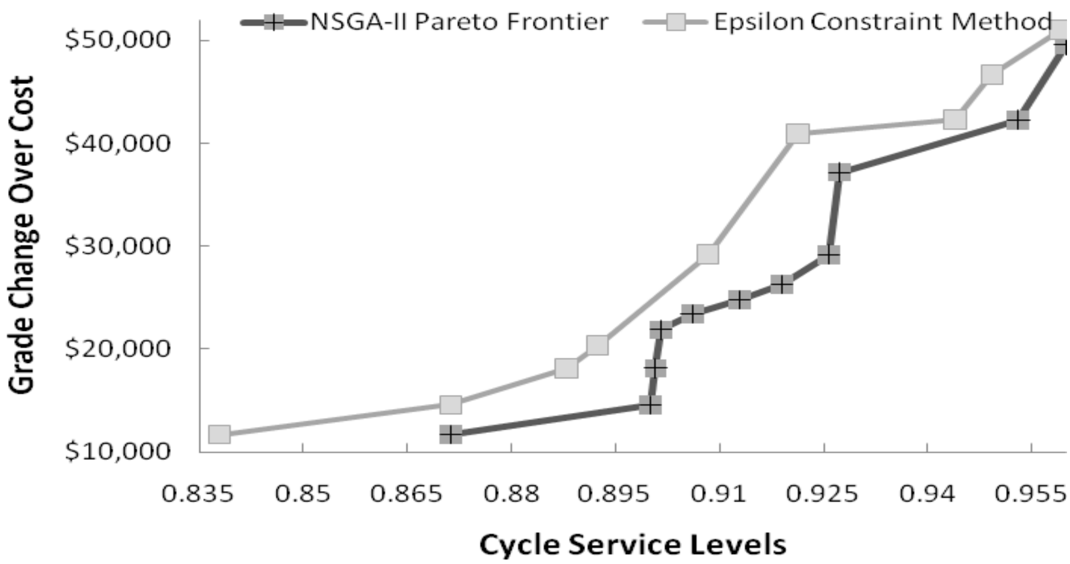

Figure 4: NSGA II Comparison with the Epsilon Constraint Results

All the solutions from the ten runs were combined and top hundred were used as the initial population to generate the best Pareto front for the problem (Figure 3). Typical of a stochastic optimizer, the last generation of all the ten NSGA II runs was different; therefore, the combination of all solutions to obtain the final frontier makes sense. As expected, the combined run that includes the best 100 solutions turns out to be the global Pareto frontier of the problem.

In figure 3, the Pareto frontier obtained by Run 5 and Run 6 appear to cross the global Pareto frontier obtained by the 'Combined Run'. However, it does not happen actually because all the points obtained by Run 5 and Run 6 are dominated by the 'Combined Run'. It is just that the Run 5 and Run 6 contain overall fewer solutions and the additional solutions of the 'combined Run' at the exact locations of the overlaps give the false impression that the Run 5 and Run 7 are better.

6. DISCUSSION

The Pareto frontier obtained by the Epsilon constraint method which is also the initial Pareto frontier is compared with the improvements recorded by the NSGA-II solutions in figure 4. All the NSGA-II solutions are equally good or better than the epsilon constraint results highlighting the fact that the Epsilon constraint method did not result in a global Pareto frontier which is not surprising because the GA experiments corresponding to one epsilon value were only performed once. It is widely regarded that only repeated GA experiments can ensure best possible solutions (Malik, Qiu & Taplin 2009). Figure 4 also shows that the NSGA-II's Pareto front stayed within the bounds obtained by the ideal and nadir objective vectors. The overall shape of the Pareto frontier also did not change much suggesting that NSGA-II was only able to find improved solution in the vicinity of the existing feasible solutions. Therefore, it appears that the initial Pareto front dictates NSGA-II's search process.

The ability of the standard genetic algorithm when applied as an epsilon constraint method to obtain feasible solutions and the inability of NSGA-II to do the same from an initial random population can be explained by the different constraint handling mechanisms for the two employed multi-objective algorithms. The standard GA uses the penalty function to handle constraints. The aim is to transform a constrained optimization problem into an unconstrained one by penalizing the objective function by a value based on the constraint violation. This is particularly useful for NP-Hard combinatorial optimization like the problem under study because the feasibility of solutions is gradually achieved by minimizing the 'soft penalties' to zero. On the contrary, NSGA-II's constraint handling mechanism has proved to be ineffective if the entire initial population is infeasible. However, injecting 30% feasible solution as part of the initial solution did improve the results.

Moreover, the bi-objective optimization of grade changeovers and corresponding cycle service levels simplifies the lot-sizing decisions. In the conventional single objective optimization, one of the important considerations for the selection of an appropriate lot-sizing model is the maximum number of products that can be manufactured in a single planning period. The lot-sizing model that corresponds to single product per planning period give poor results with regards to the cycle service levels but there are cost savings. When multiple products are allowed in each planning period, the cycle service levels are maximized with increase in costs. In bi-objective optimizations, there is no need to make a prior decision regarding number of products in each planning period. Multiple lot-sizing models have been integrated in to one experiment and the resulting Pareto frontier gives the production manager a range of options to choose from, depending upon the decision context.

7. CONCLUSION AND DIRECTION FOR FUTURE RESEARCH

In this paper, a multi-objective optimization approach is advocated for the successive manufacturing processes of the paper industry supply chain. A two step solution approach is proposed to the bi-objective production planning problem. In the first step, a set of non-dominated solutions is obtained by employing the epsilon constraint method which is used a part of initial population for the NSGA-II in the second step. NSGA-II not only improves the quality of epsilon constraint solutions but also increases the number of solution on the Pareto frontier. Issues associated with the successful implementation of the multi-objective optimization algorithms were discussed and the importance of estimating the ideal and nadir objective vector to reflect the entire set of feasible search space was highlighted.

The relevance of multi-objective optimization approach to the real world situation such the production planning problem understudy is stressed. Ideally, the mill would like to run long production runs with minimum grade changeovers and to cut the jumbo reels to stock in anticipation of customer demand. The same decision context prevailed in yesteryears but ever increasing customer requirements and marker pressures now warrant a trade-off between production cost, flexibility and customer service. Typically, in paper industry, while some customers enjoy considerable leverage on the paper mill and will insist on having their orders delivered in time because of their own constraints, the paper mill can also afford to delay some orders by being flexible with a few of its customers for order delivery, therefore, saving on production costs. The cost reduction by compromising on the service levels can be an advantage for both the supplier and customers. For the customers insisting on punctual deliveries, the bi-objective formulation discussed in this paper gives a useful tool to the mill manager because it can help to quantify the associated extra cost.

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