MRP LOT SIZING USING GENETIC ALGORITHMS

D.J. Stockton, and L. Quinn, De Montfort University

ABSTRACT

This paper describes initial efforts to use genetic algorithms to develop a multi-level MRP lot sizing technique. Initially the limitations of existing lot sizing techniques are explained. Such methods are seen to determine lot sizes for individual items at only a single level in a BOM structure and hence by default assume that item demand is independent. The essential procedures used in genetic algorithms are then explained using an example MRP lot sizing problem. This example clearly illustrates the multi-level lot sizing potential of genetic algorithms. Order release schedules are then determined using genetic algorithms and for comparison purposes the McLaren's Order Moment method. The results are then used to identify the effectiveness of the genetic algorithm method for determining MRP lot sizes.

KEY WORDS

MRP, Genetic Algorithms, Multi-level lot sizing, McLarens Order Moment

EXISTING MRP LOT SIZING TECHNIQUES

Material Requirements Planning is now an accepted method of planning the material requirements for items whose demand is dependant on higher level items within the Bill of Material, (BOM), structure.

The planning process starts with a production schedule and then applies MRP logic through BOM's and inventory records as indicated in Figure 1. The planned order releases that are output from the MRP process are those required to provide the quantity of items necessary to satisfy planned production requirements within each time bucket. Ideally MRP must be capable of producing a planned order receipt schedule such that this schedule minimises the total costs of holding and purchasing inventory over the entire planning horizon. In addition the inventory demands for each period within that planning horizon must be met such that there are no stock-outs in any period.

The aim of the MRP process is to determine the orders that need to be released in order that planned production can take place. Two items of information constitute a planned order release for a particular item ie:

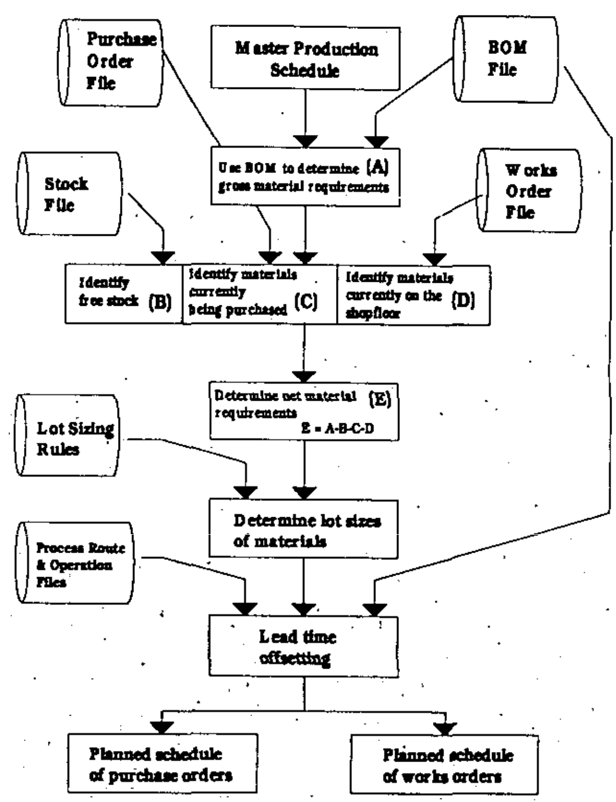
- an order size
- an order release date

Although the logic underlying the MRP process is simple the results of the process can have a profound effect on the profitability of an organisation. In this respect the lot sizes chosen for the highest level components determine the quantities of lower level items required. Complex demand relationships can often exist between such items.

There are a wide variety of MRP lot sizing techniques that are currently available. Wagner and Whitin [1] for example developed a procedure using dynamic programming as early as 1958 which is still recognised as one of the only methods available that can consistently generate least cost lot sizing conditions. Techniques vary from simple decision rules, (in which little effort is made to optimise the decisions made), to complex procedures that attempt to develop optimum planned order release schedules. Lot sizing techniques in current use are of three basic types [2], ie:

FIGURE 1

THE MRP PROCESS



1. Based on the Economic Order Quantity, (EOQ), model. Such models include the use of the EOQ model to determine either a specific lot size to purchase or a frequency with which batches should be purchased, ie. the Periodic Order Quantity, (POQ). The POQ model determines the time when an order should be placed and the actual quantity ordered is that quantity required between the placement of two successive orders. The use of the EOQ method results in a constant batch size being ordered whereas the POQ method allows the ordered batch size to vary.

2. Single pass methods, of which there are a wide variety, are essentially ruled based. Each individual method applies a unique set of rules to determine schedules for order releases. Such methods include the Lot-For-Lot rule, (LFL), Least-Total-Cost, (LTC), Least-Unit-Cost, (LUC), and many others such as those developed by Silver and Meal, [3], Groff, [4], Freeland and Colley, [5] and Bahl and Zionts, [6].

3. Adjusted single pass methods initially make use of a specific single pass technique and then attempt to improve on the solution produced by this technique. This is achieved by examining the total costs involved in either increasing batch sizes such that the materials for one or more additional periods may be purchased, (ie. termed 'look ahead'), or decreasing purchase batch sizes to remove periods from the decision making process. If the total costs can be reduced by these actions then the new batch sizes are adopted.

Choosing which technique to use from the wide variety available is a major problem for materials managers since each technique will only yield acceptable results under a limited range of demand and inventory cost conditions. Recognising the need for materials managers to choose between the many techniques available Berry [7] developed a framework for comparing such methods in terms of their ability to minimise inventory related costs over a range of cost and demand parameter values. In addition Berry proposed that this framework should also include comparisons of the amount of computing time required to make lot sizing decisions and estimates of the simplicity of the procedures used. Since this framework became available a number of researchers [8, 9] have provided comparisons of existing techniques over a wide range of conditions whilst others [10, 11, 12] have concentrated on developing improved lot sizing algorithms. However the techniques developed have again been limited in their application areas. Gaither [13] for example presented a technique that identified near-optimal MRP lot sizes and possessed procedural simplicity. However this model was found to exhibit a built-in bias towards larger batch sizes when high 'ordering cost to carrying cost' ratios existed. The procedures used, therefore, had to be modified [14] to compensate for this defect. This indicates that the limitations involved in using existing lot sizing techniques are not always immediately obvious.

LIMITATIONS OF EXISTING LOT SIZING METHODS

Existing methods have many fundamental problems that limit their usefulness in practical situations. For example those methods that seek optimal schedules do so by considering all available options. As the MRP planning horizon grows larger the number of alternative schedules that need to be compared dramatically increases. This results in excessive computations being required. In order to obtain optimal schedules, therefore, MRP planning horizons must be limited. Hence optimal short term schedules are obtained but these individual schedules do not necessarily result in optimisation of inventory over the long term. Generating optimal or near optimal schedules requires the use of complex procedures that are often difficult for operating personnel to understand. Their use within manufacturing industry is often limited for this reason.

A critical appraisal was carried out by St John [15] who highlighted major misconceptions in the evaluation of existing lot sizing techniques. He argued correctly that the majority of the current methods in use are not applicable to MRP since:

1. They treat the lot sizing problem as a single stage process, ie. determine lot sizes for single items. MRP is, however, a multi-stage process and any lot sizing techniques must take into consideration the relationships between items. Such methods must consider all items whose demand is related, both horizontally and vertically, to each other via the BOM structures. MRP items, therefore, exhibit dependent demand patterns whereas current lot sizing methods apply only to independent demand patterns.

2. Each individual technique is valid, (ie. produces acceptable order schedules), under a particular set of conditions. The effectiveness of a technique for example is strongly dependent on such factors as the variability in the sizes of individual material requirements, the variability in the frequency of requirements, and the relative values of carrying and purchasing costs. In order to achieve good results, therefore, it is necessary to select with care the most appropriate method from amongst the many available. Since the demand and cost parameters for individual items within a BOM may vary, then ideally the most appropriate method for each item should be selected. This is obviously impossible due to lack of resources and in practice a specific lot sizing technique is often applied to a group of items irrespective of how suitable it is for individual items within that group. Demand over time is not necessarily constant, ie. lumpy demand patterns can exist. This is particularly true when a company's products exhibit seasonal bias in which case there can be months when there is no demand, months when there is little demand and months when demand reaches its peak. Choosing a specific lot sizing method for each item/demand period is again clearly impractical since regular checks would, therefore, need to be carried out to ensure that changes had not occurred that adversely effected the suitability of the technique being used.

3. All existing methods use costs to measure how effective a specific lot sizing policy is. Many methods place restrictions on the types of costs that are considered. In general the emphasis is on minimising the combined order/set-up and carrying costs. It is uncommon, when determining lot sizes, for non-cost variables such as the availabilities of working capital for purchasing stock or warehouse space to be considered. Hence situations can occur in which there is insufficient working capital or storage space to support the purchasing decisions made by a MRP system.

4. MRP systems often provide a range of lot sizing techniques. Choosing which technique to select often looks a routine decision since the likely results of such a change are not adequately identified. Changing lot sizing techniques in this way can often lead to disastrous consequences, in particular excessive stockholding costs being incurred.

5. The use of existing dynamic lot sizing techniques can lead to system nervousness which occurs when relatively minor changes in the order schedule of a higher level component causes significant changes to the order schedules of lower level items. MRP nervousness is, therefore, the amplification of minor changes which create such conditions as late orders. Vollmann et.al [16] suggested that the use of different lot sizing techniques at different levels in the BOM structure would assist in reducing the effects of nervousness. However, this would result in the choice of a suitable lot sizing technique becoming even more difficult.

Despite St John's condemnation of existing lot sizing techniques research has still focused on the comparison of lot sizing techniques and the development of more efficient single item, independent demand methods. Nydick and Weiss [2] for example compared ten lot sizing techniques and evaluated them using a variety of demand and order cycles. They concluded that 'the greater the variability in the pattern of demand, and the more frequent the order cycle the more erratic is the behaviour of all lot sizing techniques in determining the optimum conditions'.

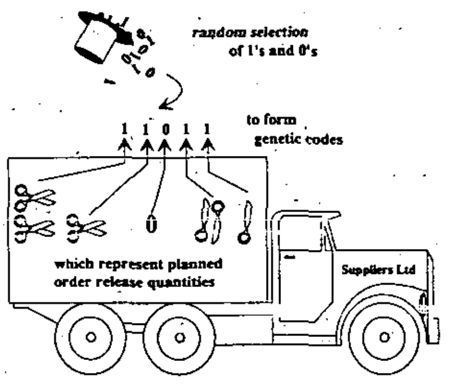
GENETIC ALGORITHMS

A general overview of the theory that forms the basis of genetic algorithms is provided by Holland [17] who has been instrumental in developing much of their mathematical structure. Essentially a 'genetic algorithm' is a set of procedures which when repeated enables solutions to be found to specific problems. They achieve this objective by generating successive populations of alternative solutions until a solution is obtained that yields acceptable or optimal results. As each successive population is generated an improvement in the quality of the individual solutions is gained. Hence a genetic algorithm can quickly move to a successful outcome without the need to examine every possible solution to the problem.

The procedures used are based on the fundamental processes that control the evolution of biological organisms. These basic processes are natural selection and reproduction which together improve an organisms ability to survive within its environment. Natural selection determines which organisms within a population survive and which, therefore, have the opportunity of reproducing. Reproduction involves genes from two separate individuals combining to form off-spring that inherit the survival characteristics of its parents and may also possess additional beneficial characteristics. *Genetic algorithms, therefore, seek to imitate the way in* which beneficial genes reproduce themselves through successive populations and hence contribute to the gradual ability of an organism to survive.

Genetic algorithms have the potential for MRP lot sizing since they have been proved to be capable of resolving large scale engineering problems in which the number of alternative solutions are great. For example Goldberg [18] describes their use to develop a system for controlling a gas pipeline that consists of large numbers of branches and valves to regulate the flow of gas. He also highlights their use in areas such as machine learning, pattern recognition, image processing and *operational research. Such algorithms can also be* used to schedule work through manufacturing systems [19, 20], determine economic lot sizes [21], develop optimal designs for engineering structures [22] and schedule students within classes [23]. Dawn [24] highlights their use in designing gas turbines, targeting potential loan defaulters and reducing the weight of jib structures. Dawn [24] also reports the work being carried out to develop GA procedures for creating optimum process plans for components manufactured within machine shops. He identifies a major benefit in using GA procedures as 'the ease with which GA's can be split up and run on parallel computers'. This facility enables problems with potentially large numbers of possible solutions to be solved *in a matter of a few minutes.*

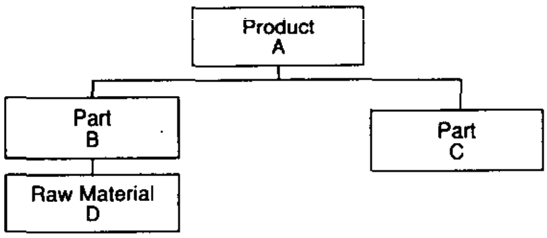
DIAGRAM 1 - GA CODING OF MRP PLANNED ORDER RELEASES



METHODOLOGY FOR MULTI-LEVEL MRP LOT SIZING

The demand relationships that exist between items in a BOM structure pose problems when developing multi-level lot sizing procedures. The essential problem is that the lot sizes selected for an item at one specific level predetermine the gross requirements for items at the next level down. For example in Figure 2 the lot size selected for item A determines the gross requirements for items B and C and subsequently all other lower level items. The problems associated with these demand relationships between BOM levels can be *resolved by ensuring that:*

FIGURE 2.
BILL OF MATERIAL STRUCTURE



1. During the multi-level lot sizing procedure checks are carried out to ensure that the lot sizes identified for lower level items meet the lot size requirements for higher level items.

2. If scheduled receipts and free stock already exist for any item in the product structure then these must be considered when setting lot sizes.

   Assume that genetic algorithms are to be used to determine a planned order release schedule for each item in the BOM *structure shown in* Figure 2. For simplicity if a three period planning horizon was assumed then the MRP process would be expected to provide after lot sizing had taken place the planned order release schedule shown in Table 1.

TABLE 1
MRP PLANNED ORDER RELEASE SCHEDULE

	MRP PLANNING PERIOD		
	PERIOD 1	PERIOD 2	PERIOD 3
MRP ITEM			
A PRODUCT	Q1	Q2	Q3
B PART	Q4	Q5	Q6
C PART	Q7	Q8	Q9
D RAW MATERIAL	Q10	Q11	Q12

The values Q1, Q2, ... Q12 are the Planned Order Release, (POR), quantities of each item in specific MRP planning periods. The traditional objective is to ensure that these quantities minimise the overall costs involved in purchasing and holding stocks. *A possible POR schedule could be as shown* in Table 2. This schedule may not represent the optimum POR's but it is necessary to represent this and other alternative schedules in the form of a genetic code.

TABLE 2
POTENTIAL POR SCHEDULE FOR PRODUCT A

	MRP PLANNING PERIOD		
	PERIOD 1	PERIOD 2	PERIOD 3
MRP ITEM			
A PRODUCT	20	10	21
B PART	16	30	36
C PART	15	25	51
D RAW MATERIAL	3	42	22

In order to represent this as a genetic code each of the batch quantities listed in the schedule must be converted from their current decimal base to their equivalent binary base. For example the binary equivalent of 20 is 010100 and that for 51 is 110011. Table 3 lists the binary numbers for all the items being considered.

TABLE 3
POR SCHEDULE REPRESENTED AS BINARY NUMBERS

MRP ITEM	MRP PLANNING PERIOD		
	PERIOD 1	PERIOD 2	PERIOD 3
	BINARY NUMBERS		
A PRODUCT	010100	001010	010101
B PART	010000	011110	100100
C PART	001111	011001	110011
D RAW MATERIAL	000011	101010	010110

The binary numbers listed in Table 3 are now connected into a single string as illustrated in Figure 3 to produce the necessary genetic code. In order to decode such a string the reverse procedure is applied, ie. split the string into six digit sections and convert each section to its equivalent decimal number. Figure 3 indicates which item/MRP period each section of the binary string applies to. Each binary number within the string represents a specific aspect of the problem solution, ie. a potential lot size for a single item in a BOM structure for a specific period of the MRP planning horizon.

FIGURE 3
GENETIC CODE FOR POR SCHEDULE

	010100	001010	010101	010000	......	010110
ITEM	A	A	A	B		D
PERIOD	1	2	3	1		3

Such a string would in practice contain many thousands of these binary numbers and would represent a single solution to the MRP lot sizing problem. Genetic algorithms would need to manipulate large numbers of these strings. In genetic algorithm terms each such string would be termed a 'solution' and a group of solutions would represent a 'population'.

Now that a POR schedule has been successfully converted into a genetic code the GA procedures may now be applied as such:

1. A population of such solutions, (ie. strings), must be randomly generated. The batch sizing problem represents no problems in this respect since the value of each digit within a specific solution string can be decided for example on the toss of a coin. In practice the use of a random number generator would be used that simply chose either 0's or 1's on a random basis. Decisions that need to be made at this stage are:

   * How many solutions should form the initial population

   * Should subsequent generations of populations have random solutions introduced

   * Should non-feasible solutions be allowed into the population, ie. those that would result for example in stock-outs occurring.

2. A 'fitness value' for each solution must then be calculated using an appropriate objective function. In this example the fitness of each solution will be determined based on how well the solution minimises holding and procurement costs. The holding and procurement costs associated with each string in the population must therefore be determined.

   This is achieved by decoding each string into its respective POR schedule and using an appropriate model to determine the costs that would arise from adopting each schedule. Table 4 illustrates this process for the POR schedule shown in Table 3. The value 1/744.5 would represent the 'fitness' of this particular solution, ie. solutions with higher total costs would have a correspondingly lower fitness value. In practice multi-objective functions may be used that could contain both quantitative and qualitative fitness criteria. Cost penalties can also be added to the fitness function of any solution in which stock-outs may occur, ie. when lot sizes for lower level BOM items do not meet the requirements of higher level items.

TABLE 4
CALCULATION OF THE FITNESS VALUE

MRP ITEM	MRP PERIOD	BINARY NUMBER	DECIMAL NUMBER (Q)	HOLDING COSTS (£'s) (Q/2) x Ch	PURCHASE COSTS (£'s) Cp
A	1	010100	20	10.0	50
A	2	001010	10	5.0	50
A	3	010101	21	10.5	50
B	1	010000	16	8.0	50
B	2	011110	30	15.0	50
B	3	100100	36	18.0	50
C	1	001111	15	7.5	50
C	2	011001	25	12.5	50
C	3	110110	51	25.5	50
D	1	000011	3	1.5	50
D	2	101010	42	21.0	50
D	3	010110	22	11.0	50
				£144.5	£600

Total Costs = £744.5
Fitness value = 1/744.5 = 0.00134

3. Once the fitness values for each solution have been determined they can be used to compare each solution and determine a solution's probability of surviving into the next generation. A simple method of accomplishing this is shown in Table 5.

TABLE 5
COMPARISON OF SOLUTIONS WITHIN A POPULATION

SOLUTION	FITNESS VALUE (£'s)	% of TOTAL
A	0.11000	23.43
B	0.01200	2.56
C	0.00120	0.26
D	0.10000	21.30
E	0.20000	42.59
F	0.00400	0.85
G	0.04000	8.52
H	*0.00134*	*0.29*
I	0.00100	0.21
	Total = 0.46954	100%

The '% of total' now represents the probability that each solution will be represented in the next generation, eg. solution H has approximately a 0.3% chance of being represented in this next population because it resulted in such large purchase and holding costs when compared with other solutions within the population.

4. The GA now involves randomly identifying a section of one solution string and swopping this over with a section from another solution string. This procedure is termed crossover and has been found to be highly effective in producing improved solutions. Figure 4 illustrates the process in operation. The first six digits from solutions H and I have been exchanged resulting in two new solutions J and K.

FIGURE 4
EXAMPLE OF A SIMPLE CROSSOVER PROCEDURE

SOLUTION H	010100	001010	010101	010000	......	010110
SOLUTION I	111001	101001	100001	100100	......	101011
SOLUTION J	111001	001010	010101	010000	......	010110
SOLUTION K	010100	101001	100001	100100	......	101011

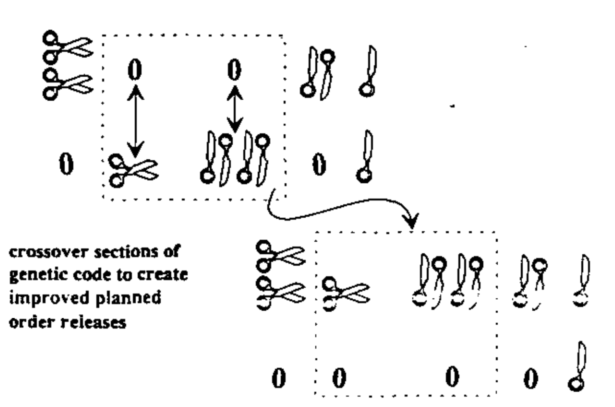
SECTION OF STRINGS CROSSED OVER

When the best features of two solutions are combined the resulting off-spring could have a much higher fitness value than either of its parents. This off-spring would, therefore, be reproduced in larger numbers into succeeding generations. When two solutions with poor features combine the low fitness value of their off-spring will result in it being lost, ie. not reproduced into succeeding generations. One of the useful characteristics of genetic algorithms is the possibility of two poor solutions combining and resulting in an off-spring with a high fitness value. Whatever the result of these combinations only those off-spring that are fit will survive to succeeding generations. Hence the algorithm quickly builds populations with good solutions to the problem being examined.

The GA procedure now continues by repeating the steps described above, ie:

i. Determining the fitness value of each solution string within a population
ii. Generating a new population from the previous population using those solutions with high fitness values
iii. Generating improved solutions using the crossover technique. Here the mathematical principles underlying the GA procedures are now well established and a variety of techniques are available for improving solutions fitness and ensuring that good sections of a solution string are not lost.

DIAGRAM 2
CREATING IMPROVED SOLUTIONS USING 'CROSSOVER'



RESULTS

Using the BOM structure shown in Table 6 and the gross requirements schedule illustrated in Table 7 the planned order release quantities were determined using the genetic algorithm procedures previously described and for comparison purposes McLaren's Order Moment [25].

TABLE 6
BILL OF MATERIALS FOR FLASHLIGHT

ITEM CODE	BOM LEVEL	DESCRIPTION	HOLDING COSTS PER UNIT (£'s)
1	0	FLASHLIGHT	32
2	1	HEAD ASSEMBLY	10
5	2	PLASTIC HEAD	2
16	3	PLASTIC - RAW MATERIAL	1
6	2	LENS	1
7	2	BULB SUB-ASSEMBLY	3
11	3	BULB	1
12	3	BULB HOLDER	1
8	2	REFLECTOR	1
4	1	BODY ASSEMBLY	15
9	2	SHELL ASSEMBLY	11
13	3	ON/OFF SWITCH	4
17	4	KNOB	1
18	4	METAL SLIDES	1
14	3	CONNECTOR BARS	1
15	3	PLASTIC SHELL	4
16	4	PLASTIC - RAW MATERIAL	1
10	2	SPRING	1
3	1	BATTERIES	3

PROCUREMENT COST PER BATCH = £100

McLaren's Order Moment, (MOM), initially generates planned order release schedules for integral numbers of future MRP periods, (eg. period 1, periods 1 and 2, periods 1, 2, and 3). In order to identify the most suitable schedule from amongst these alternatives the MOM uses the part period accumulation principle, (ie. a part period is equivalent to one unit of stock carried for one MRP period). The selected schedule's accumulated part periods must match the number of part periods that would be incurred if an EOQ batch size had been calculated under conditions of constant demand. Comparison studies [26] have found that the MOM procedure produces lower cost order schedules when compared with the main methods in common usage, ie. Part Period Balancing, Periodic Order Quantity and Economic Order Quantity.

TABLE 7
GROSS REQUIREMENT SCHEDULE FOR FLASHLIGHT

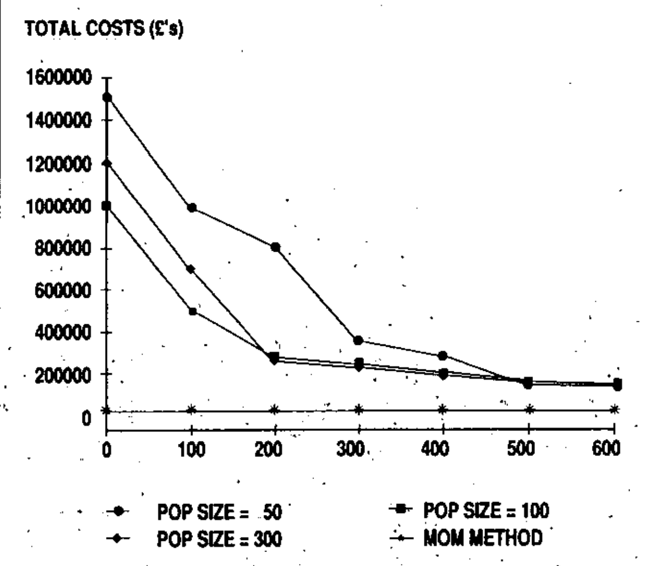
MRP PLANNING PERIOD	1	2	3	4	5	6	7	8	9	10	11	12
GROSS REQUIREMENTS	10	10	15	20	70	180	250	270	230	40	0	10

The procedures for determining order release schedules using GAs were developed using the Genesis software [27]. This software programme was written to encourage the experimental use of genetic algorithms for function minimisation. The genetic algorithm functions provided are task independent. Hence users need only provide evaluation functions for determining the fitness of individual solutions within a population. The Genesis programme then contains functions for:

1. Initialisation, ie. setting-up the initial population
2. Selection, ie. choosing solutions for the next generation from the solutions in the current generation
3. Crossover, ie. exchanging sections of one solution with those of another to produce different solutions.

GA trials were carried out using various population sizes, ie. 50, 100 and 300. The trials involved running the GA procedures for up to 600 generations. The lowest cost solution from each generation was then used to produce Figure 5. In addition the result obtained using the MOM technique has also been included for comparison purposes.

FIGURE 5
COMPARISON OF GA AND MOM RESULTS



DISCUSSION

The results shown in Figure 5 indicate the ability of genetic algorithms to breed improved solutions from one generation to the next. Trials were carried out in which the size of the population was altered, (ie. population sizes of 50, 100 and 300). Again Figure 5 indicates the effect of changing this variable, ie. essentially there is a greater chance of lower cost solutions being in the initial population and these are regenerated into succeeding populations. The trials carried out using genetic algorithms all converged to produce order release schedules with greater total costs then obtained using the MOM method. This is partly due to the simplicity of the MRP lot sizing problem examined, ie. the MOM procedure is capable of obtaining optimal or near optimal solutions for a problem of this size. However, MOM as with other existing MRP lot sizing methods are single level procedures and the benefits of using such methods would quickly disappear as the complexity of the BOM structures increased and as the number of MRP periods increased.

The effectiveness of the GA procedure on the other hand would not be expected to decline since the method has already been shown to solve problems with large numbers of possible solutions. GA procedures are, however, dependent on how well various parameters have been selected. Future work is now being directed towards identifying improved cross-over techniques and methods of generating future populations, both of which can have a considerable effect on the efficiency of GA procedures. In addition the use of 'coarse sieves' are being examined in which lot sizes are restricted to specific multiples, (eg. multiples of 10, 20 or 100), in order to enable the solution space to be quickly searched for low cost solutions. Once these initial solutions have been identified these will then form the solutions for the initial populations of more refined GA procedures.

Perhaps of most benefit to enabling GAs to solve MRP problems of a practical nature would be the availability of large amounts of parallel computing power. The natural parallel character of the genetic solution codes themselves could then be employed to ensure that such MRP lot sizing problems could be solved in short amounts of time.

Research is continuing in this area since there are overwhelming advantages to be gained in using GA procedures, ie:

1. Current methods of determining MRP lot sizes can only be used under limited conditions hence complex inventory management policies cannot be resolved. Objective functions used in the GA procedure, however, can be complex and need not be restricted to optimising individual functions. In addition objective functions used may consider criteria other then costs, such as delivery lead times or quality levels. The types of cost elements used are not restricted, ie. marginal costs can be used if required. Objective functions can also include both quantitive and qualitative variables.

2. The GA procedure generates populations of solutions and can provide total annual cost information for each solution. Management, therefore, are provided with the opportunity of selecting non-optimum order release schedules if by doing so other problems can be simplified. For example order release schedules may be selected that are convenient for shop floor scheduling purposes. Management can make these decisions knowing the additional costs involved when compared with the optimum batch size.

3. 'Nervousness' would not arise since all components are considered simultaneously.

4. The same procedures could be used whatever the demand pattern, order and holding costs, order cycles, lengths of planning horizons and demand distributions. Hence the problem of selecting the best lot sizing method to use would no longer arise. In addition it would not be necessary to monitor the method used to ensure that any changes taking place in the environment had adversely affected the use of the model.

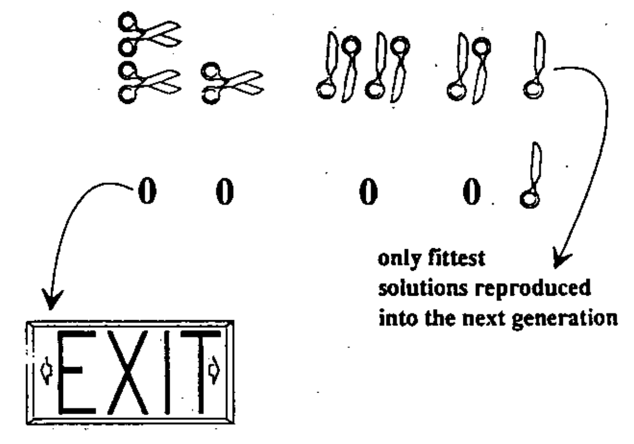
5. No assumptions need be made concerning such variables as demand and usage rates as with EOQ.

6. The method would not be restrictive in the number of MRP planning periods it could take into consideration.

7. It would not rule out the possibility of combining orders for successive periods when demand is low.

8. It could enable both the lot size and the time between orders to vary.

DIAGRAM 3
SURVIVAL OF THE FITTEST



REFERENCES

[1] H.M.Wagner and T.M.Whitin, "Dynamic Version of the Economic Lot Size Model", Management Science, October, 1958, pp 89-96.

[2] R.L.Nydick and H.J.Weiss, "An Evaluation of Variable-demand Lot-sizing Techniques", Production and Inventory Management Journal, 4th Quarter, 1989, pp 41-44.

[3] E.A.Silver and H.C.Meal, "A Heuristic for Selecting Lot-sizing Quantities for the Case of Deterministic Time-varying Demand Rate and Discrete Opportunities for Replenishment", Production and Inventory Management, 14,2, 1973, pp 64-74.

[4] G.Groff, "A Lot-sizing Rule for Time-phased Component Demand", Production and Inventory Management, 20,1, 1979, pp 47-53.

[5] J.R.Freeland and J.L.Colley, "A Simple Heuristic Method for Lot Sizing in a Time Phased Re-order System", Production and Inventory Management, 23,1, 1982, pp 14-22.

H.C.Bahl and S.Zionts, "Lot Sizing as a Fixed-charge Problem" Production and Inventory Management, 27,1, 1986, pp 1-10.

[7] W.L.Berry, "Lot Sizing Procedures for Requirements Planning Systems: A Framework for Analysis", Production and Inventory Management, 2nd Quarter, 1972, pp 19-34.

[8] S.Axsater, "Evaluation of Lot Sizing Techniques", International Journal of Production Research, 24,1, 1986, pp 51-57.

[9] T.F.Callarman and R.S.Hamrin, "A Comparison of Dynamic Lot Sizing Rules for Use in a Single Stage MRP System with Demand Uncertainty", International Journal of Operations and Production Management, 4,2, 1984, pp 39-48.

[10] B.J.Coleman and M.A.McKnew, "An Improved Heuristic for Multilevel Lot Sizing in Material Requirements Planning", Decision Science Journal, 22,1, 1991, pp 136-156.

[11] D.C.Aucamp, "A Variable Demand Lot-Sizing Procedure and a Comparison with Various Well-known Strategies", Production and Inventory Management, 26,2, 1985, pp 1-20.

[12] W.C.Benton, "Multiple Price Breaks and Alternative Purchase Lot Size Procedures in Material Requirements Planning Systems", International Journal of Production Research, 23,5, 1985, pp 1025-1047.

[13] N.Gaither, "A Near-optimal Lot-sizing Model for Material Requirements Planning Systems", Production and Inventory Management, 4th Quarter, 1981, pp 75-89.

[14] N.Gaither, "An Improved Lot-sizing Model for MRP Systems", Production and Inventory Management, 3rd Quarter, 1983, pp 10-20.

[15] R.St John, "The Evils of Lot Sizing in MRP", Production and Inventory Management, 4th Quarter, 1984, pp 75-85.

[16] T.E. Vollmann, et,al, "Manufacturing Planning and Control Systems", 3rd Edition, 1992, Irwin.

[17] J.Holland, "Genetic Algorithms", Scientific American, 267/1, July, 1992, pp 44-50.

[18] D.E.Goldberg, "Genetic Algorithms in Search, Optimization and Machine Learning", Addison-Wesley, Massachusetts, 1989.

[19] L.Davis, " Job Shop Scheduling with Genetic Algorithms", Proceedings of the International Conference on Genetic Algorithms, 1985, pp 136-140.

[20] G.A.Cleveland and S.F.Smith, "Using Genetic Algorithms to Schedule Flow Shop Releases", Proceedings of the Third International Conference on Genetic Algorithms, 1989, pp 160-169.

[21] D.J.Stockton and L.Quinn, "Identifying Economic Order Quantities using Genetic Algorithms", International Journal of Operations and Production Management, Vol. 13, No. 11, 1993. To be published

[22] D.E.Goldberg and M.P.Samtani, "Engineering Optimization via Genetic Algorithm", Electronic Computation Proceedings of 9th Conference, 1986, ASCE, New York, ISBN 0872625125, pp 471-482.

[23] L.Davis and F.Ritter, "Schedule Optimization with Probabilistic Search", Proceedings of the 3rd IEEE Conference on artificial intelligence", 1987, pp 231-236.

[24] T.Dawn, "Reproduction Benefits Production Scheduling", Professional Engineering, October 1992, pp 38-39.

[25] B.J.McLaren, " A Study of Multiple Level Lot Sizing Techniques for Material Requirements Planning Systems", PhD Thesis, Purdue University, 1977.

[26] U.Wemmerlov and D.C.Whybark, " Lot Sizing under Uncertainty in a Rolling Schedule Environment", International Journal of Production Research, 22,3, 1984, pp 467-484.

[27] J.J.Grefenstette and N.N.Schraudolph, "A Users Guide to Genesis 1.2uscd, Navy Center for Applied Research in Artificial Intelligence, Naval Research Laboratory, Washington, 1990.

About the Authors

David Stockton is a principal lecturer and head of the Manufacturing Systems Research Group within the Department of Mechanical & Manufacturing Engineering at De Montfort University. He has previously worked in the technical, sales and production areas of several large manufacturing organisations. In addition to his research and teaching duties he currently has responsibility for the management of several teaching companies.

Mr. Liam Quinn is a researcher within the Department of Mechanical and Manufacturing Engineering at De Montfort University and is currently developing software for the automatic design of manufacturing and logistic systems. He has been closely involved in the organisation of a DTI manufacturing intelligence club within the East Midlands. He gained an MSc. from the University of Birmingham. He has previously been involved in the development of computer systems for product tracking and modelling transport networks.