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Teaching Learning Based Optimization Approach for the Development of an Effective Master Production Schedule

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Abstract— Manufacturing industry is always a challenging area because of the unpredictable uncertainties and obstacles that might occur anytime throughout the operation. For an effective and efficient synchronization of operations in any such organization, a Master Production Schedule (MPS) is necessary. The overall objective of MPS is to allocate all the manufacturing resources in an efficient manner while satisfying the forecasted demands. Hence, MPS is a plan that determines optimal values of products to be produced. More competitive and optimal solutions can be obtained by the nature inspired population based algorithms. Teaching-Learning-Based Optimization (TLBO) is one such recently proposed population based algorithms which does not require any algorithm-specific control parameters. This techniques is not proposed by any of the earlier researchers to create an optimum master production schedule. The work presents the development and use of TLBO to MPS problems, which is not yet found in the literature so far. The TLBO algorithm developed is applied to a benchmark problem and the research demonstrates that use of TLBO yields the most optimal solution for MPS problems when compared to Genetic Algorithm approach.

Keywords— Master Production Scheduling, Multi-objective Optimization, Evolutionary Algorithms, Teaching-Learning-Based Optimization.

I. INTRODUCTION

The difficulty in optimization of engineering problems has given way to the development of an important heuristic search algorithmic group namely, the Evolutionary Algorithm group. The most commonly used evolutionary optimization technique is the Genetic Algorithm (GA) [1]. Though, the GA provides a near optimal solution for complex problems, it requires a number of control parameters in advance which affect the effectiveness of the solution. Determining the optimum values for these controlling parameters is very difficult in practice. Considering this fact, Recently, Rao et al. & Rao and Patel have introduced the Teaching-Learning-Based Optimization (TLBO) algorithm that does not require any algorithm specific parameters [2], [3], [4]. TLBO is developed based on the natural phenomena of teaching and learning process of a classroom. TLBO contains two phases namely the teacher phase and the learning phase [5]. Similar to any population based algorithms, the TLBO also contains population. Solution vectors are the learners and dimensions of each vector is termed as a subject. Best learner in the population is a teacher [6]. The work presents the development and use of Teacher Learner based Optimization (TLBO) technique to Master production scheduling (MPS) problems, something that does not seem to have been done so far.

Master production scheduling has been extensively investigated over the last three decades and it continues to attract the interest of both the academic and industrial sectors. One must ensure that the proposed MPS is valid and realistic for implementation before it is released to real manufacturing system [7]. In this connection, several studies have suggested an authentication process to check the validity of tentative MPS, few of which include the works of [8], [9], [10]. Besides the substitution of the verification process, to solve and enhance MPS quality, researchers also have employed various advanced optimization techniques viz.; Vieira et al applied simulated annealing [11], Soares et al [12] introduced new genetic algorithm structure, Vieira [13] has compared genetic algorithms and simulated annealing for master production scheduling problems and Radhika et al [14] , [15] applied differential evolution . The objectives considered are minimized inventory level, maximize service level, minimize inventory level below safety stock and minimize overtime. The subsequent section explains the procedure of TLBO.

II. METHODOLOGY

Teaching-Learning-Based Optimization (TLBO) is a simple evolutionary algorithm which does not require any program specific parameters compared to other existing evolutionary algorithms .TLBO contains two phases namely the teacher phase and the learning phase. Similar to any population based algorithms, this algorithm also contains population.

Solution vectors are the learners and dimensions of each vector is termed as a subject. Best learner in the population is a teacher. The process of TLBO is as follows [16].

A. Initialization

The population X, is randomly initialized by a given data set of n rows and d columns using the following equation.

$$X_{i,j}(0) = X_j^{\min} + rand(1) * \left(X_j^{\max} - X_j^{\min}\right) \tag{1}$$

Xi,j Creation of a population of learners or individuals. The ith learner of the population X at current generation t with d subjects is as follows,

$$X_i(t) = \left[X_{i,1}(t), X_{i,2}(t), ..., X_{i,d}(t)\right] \tag{2}$$

B. Teacher Phase

The mean value of each subject, j, of the population in generation t is given as

$$M(t) = [M_1(t), M_2(t), ..., M_d(t) \tag{3}$$

The teacher is the best learner with minimum objective function value in the current population. The Teacher phase tries to increase the mean result of the learners and always tries to shift the learners towards the teacher. A new set of improved learners can be generated by adding a difference of teacher and mean vector to each learner in the current population as follows.

$$X_i(t+1) = X_i(t) + r * (X_{best}(t) - T_F M(t)) \tag{4}$$

TF is the teaching factor with value between 1 and 2, and ri is the random number in the range [0, 1]. The value of TF can be found using the following equation (5)

$$T_F = round(1 + rand(1)) \tag{5}$$

C. Learner Phase

The knowledge of the learners can be increased by the interaction of one another in the class. For a learner, i, another learner is selected, j, randomly from the class.

$$X_i(t+1) = \begin{matrix} X_i(t) + r * (X_i(t) - X_j(t)), iff\ ((X_i(t)) < f(X_j(t)) \\ X_i(t) + r * (X_j(t) - X_i(t)), iff\ ((X_j(t)) < f(X_i(t)) \end{matrix} \tag{6}$$

The two phases are repeated till a stopping criterion has met. Best learner is the best solution in the run.

D. Learner Representation

The proposed algorithm's population contains several learners. Each learner is in three dimensions to represent the individual solution. Fig1 shows the conceptual model of the learner for a scenario with products, resources, and periods. A set of chromosomes composing the chromosome group represents the total distribution of quantities to be made of all the products at every resource, in a given time period.

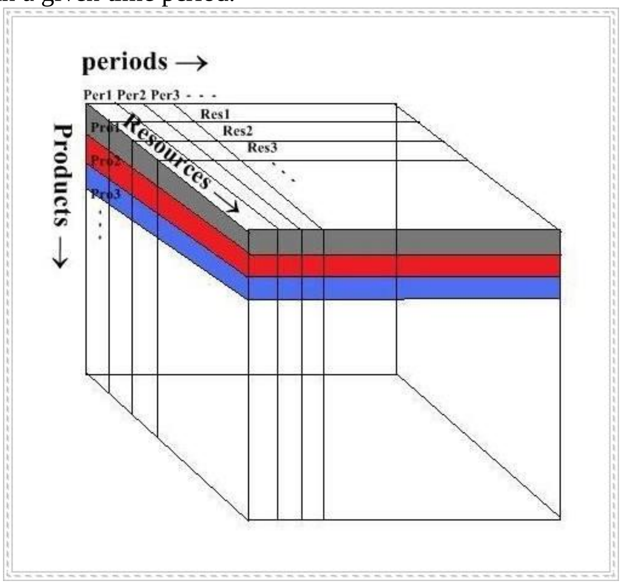


Fig. 1 Representation of a learner

E. Initial Population Criteria

Here, the population individuals are filled up randomly, with values ranging from zero to the maximum Gross Requirement (GR) for the time period. These values always respect the standard batch (lot) size restriction (i.e., they are always multiples of the standard lot size).

F. Stopping Criteria

The convergence of the algorithm is based on the fitness value of the fittest individual. The stopping criteria in the present work is "Stop by convergence or stagnation". Stopping criteria is said to be reached when the difference between fitness value of fittest individuals in any two successive generations is less than 0.0001.

III. MATHEMATICAL MODEL

The Master Production Schedule problem can be mathematically modeled as a mixed integer problem as follows Soares et al [12]:

Minimize: $$Z = c_1 EI + c_2 RNM + c_3 BSS \tag{7}$$

where,

$$EI = \sum_{k=1}^{K} \left(\frac{\sum_{p=1}^{P} EI_{kp}}{TH} \right) \tag{8}$$

$$RNM = \frac{\sum_{k=1}^{K} \sum_{p=1}^{P} RNM_{kp}}{TH} \tag{9}$$

$$BSS = \frac{\sum_{k=1}^{K} \sum_{p=1}^{P} BSS_{kp}}{TH} \tag{10}$$

$$OC = \sum_{r=1}^{R} \sum_{p=1}^{P} OC_{rp} \tag{11}$$

$$TH = \sum_{r=1}^{P} TH_p \tag{12}$$

$$BI_{kp} = \begin{cases} OH_k se(p=1) \\ EI_{k(p-1)} se(p>1) \end{cases} \tag{13}$$

$$EI_{kp} = \max[0, ((MPS_{kp} + BI_{kp}) - GR_{kp})] \tag{14}$$

$$MPST_{kp} = \sum_{r=1}^{R} MPS_{kpr} \tag{15}$$

$$MPS_{kpr} = BN_{kpr} \times BS_{kpr} \tag{16}$$

$$RNM_{kp} = \max[0, (GR_{kp} - (MPST_{kp} + BI_{kp}))] \tag{17}$$

$$BSS_{kp} = \max[0, (SS_{kp} - EI_{kp})] \tag{18}$$

$$CUH_{rp} = \sum_{k=1}^{K} \frac{(BS_{kp} \times BN_{kp})}{UR_{kr}} \tag{19}$$

$$CUH_{rp} \le AC_{rp} \tag{20}$$

MPS problem is posed as a multi-objective optimization problem. For the optimization of the selected parameters the following multi-objective criteria is selected as the fitness function [12].

$$fitness = \left[\frac{1}{1+Z_n} \right] \tag{22}$$

Where $$Z_n = c_1 \frac{EI}{EI_{\max}} + c_2 \frac{RNM}{RNM_{\max}} + c_3 \frac{BSS}{BSS_{\max}} \tag{23}$$

EImax, RNMmax and BSSmax are the biggest values found from the initial population created. Unit values are used for the fitness coefficients c1, c2 and c3 — which indicate equal importance among the objectives to be minimized. A manufacturing scenario is selected from [12] to study the applicability of TLBO algorithm for the MPS problem as follows.

The scenario is with a planning horizon of 13 periods, four productive resources, and 20 different products. The scenario also considered (a) different period lengths (b) different initial inventory quantity for each product and (c) different safety inventory levels and different standard production lot sizes.

Table1 Initial inventory and gross requirements for scenario

		Gross Requirements												
	Init.	Periods												
Products	**Inventory**	1	2	3	4	5	6	7	8	9	10	11	12	13
Product1	100	150	70	70	130	70	600	11400	700	7000	14000	700	7000	14000
Product2	0	70	50	70	60	40	700	700	400	7000	7000	400	7000	7000
Product3	300	70	100	0	70	100	0	600	1000	0	6000	1000	0	6000
Product4	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product5	100	150	70	70	150	60	700	400	2000	6000	14000	600	6000	14000
Product6	0	70	50	70	70	40	600	700	400	7000	7000	400	7000	7000
Product7	300	70	100	0	60	100	0	600	1000	0	6000	1000	0	6000
Product8	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product9	100	100	50	60	140	70	600	1400	700	7000	14000	700	7000	14000
Product10	50	60	40	70	60	40	700	700	400	7000	6000	400	7000	6000
Product11	100	150	70	70	130	70	600	1400	700	7000	14000	700	7000	14000
Product12	0	70	50	70	60	40	700	700	400	7000	7000	400	7000	7000
Product13	300	70	100	0	70	100	0	600	1000	0	6000	1000	0	6000
Product14	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product15	100	150	70	70	150	60	700	400	2000	6000	14000	600	6000	14000
Product16	0	70	50	70	70	40	600	700	400	7000	7000	400	7000	7000
Product17	300	70	100	0	60	100	0	600	1000	0	6000	1000	0	6000
Product18	50	50	0	150	50	0	1700	500	0	13000	5000	0	13000	5000
Product19	100	100	50	60	140	70	600	1400	700	7000	14000	700	7000	14000
Product20	50	60	40	70	60	40	700	700	400	7000	6000	400	7000	6000

IV. RESULTS AND DISCUSSION

The plot on Fig 2 shows the variations of fitness evolution in all the 65 independent runs. The best fitness value 0.926713 is obtained in the 2nd run and the worst fitness value 0.830392 is obtained in the 16 th run. From the figure 3, it is evident that the average fitness obtained from TLBO, is increased by nearly 25% to that obtained with MPS GA[12] and the average number of iterations taken for the convergence is 4.

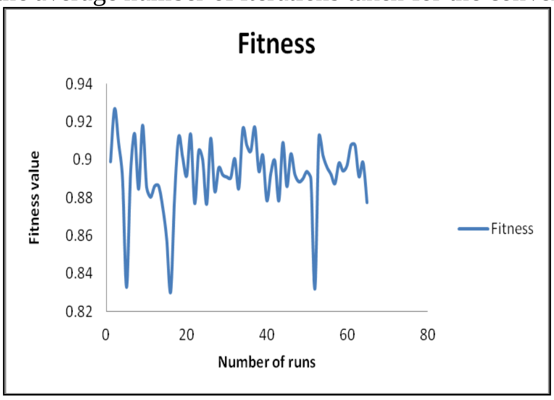


Fig.2 Evolution of fitness values

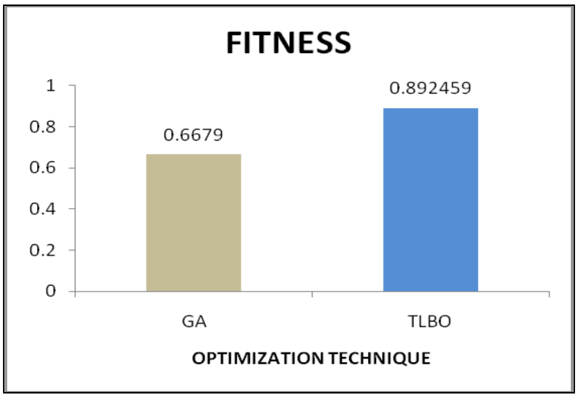
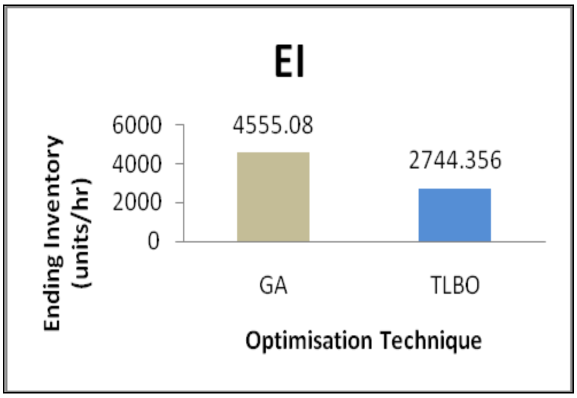


Fig. 3 Comparison of average fitness values

In general, more service levels could be attained by minimizing the RNM. But to achieve this, EI levels need to be kept a bit high. MPS GA have given a result of 321.4 units of RNM with 4555 units of EI. But the proposed MPS with TLBO could further reduce the RNM levels to 317 units and at the same time with a remarkable reduction in the EI levels. This can be seen in the figures 4 (a) and 4(b).



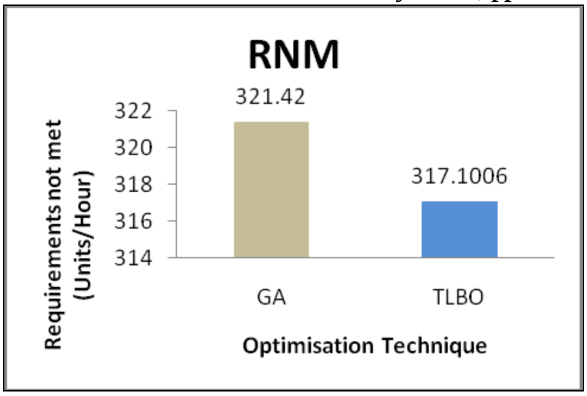


Fig 4(a), (b).Comparison of average values of Ending Inventory and Requirements Not Met

For further analysis, two cases are considered by varying the weights allotted to the performance measures. This also gives a chance of knowing as to which measure greatly influences the fitness value. In case 1, more weight is assigned to RNM (ie trying to provide more efficient service level) and in case2, more weight is assigned to the EI levels.

Table2. Comparison between the average values of performance indicators

	MPS GA	MOMTLBO		
		Equal weights	Case1	Case2
FITNESS	0.6679	0.892459	0.93367	0.91746
EI (units/hour)	4555.08	2744.35	634.6	2393.9
RNM (units/hour)	321.42	317.101	586.9	612.9
BSS (units/hour)	37.03	9.1168	13.6	9.5

In case1, the improvement of EI over MPSGA is 86.1% and that in case2 is 47.2%. This could be achieved with a much better fitness (almost 38% improvement in both the cases). As there isn't much change in the levels of BSS obtained, we can conclude that the value of fitness is greatly affected by the RNM & EI values. The average values obtained in line with the existing values are shown in the figures 5 and 6.

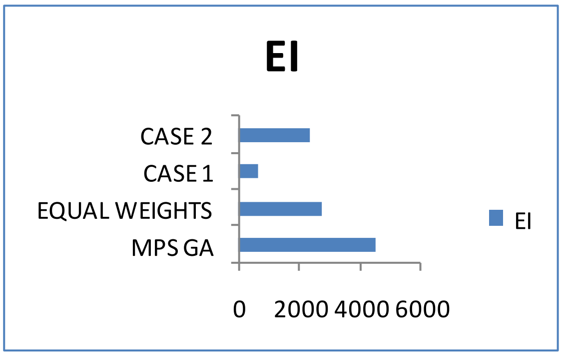


Fig. 5 Comparison of RNM values

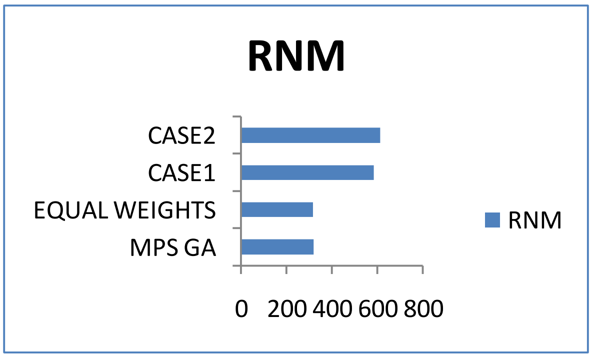


Fig. 6 Comparison of EI values

The best master production schedule found with respect to the 4 resources, 13 periods for all the 20 products along with the total MPS (TT. MPS) for each product is shown in the Table3.

Table 3. Best MPS found using TLBO

Products	Resources	Periods												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Product 1	Res1	0	0	0	0	0	0	0	0	0	11460	0	7000	0
	Res2	150	0	70	90	0	0	11400	0	2000	14000	0	7000	2000
	Res3	90	0	30	0	70	0	6030	700	0	260	0	100	0
	Res4	0	70	20	0	70	0	2210	700	7000	0	700	4600	14000
	total MPS	**240**	**70**	**120**	**90**	**140**	**0**	**19640**	**1400**	**9000**	**25720**	**700**	**18700**	**16000**
Product 2	Res1	0	40	0	10	0	0	700	0	0	5030	0	1400	1000
	Res2	70	10	0	0	40	0	700	0	7000	7000	0	3900	0

	Res3	50	0	40	0	0	0	10	0	7000	0	0	7000	0
	Res4	0	0	0	60	0	0	0	400	2000	1720	400	0	7000
	total MPS	**120**	**50**	**40**	**70**	**40**	**0**	**1410**	**400**	**16000**	**13750**	**400**	**12300**	**8000**
(For conciseness, MPS for products 3 thru 18 are not shown)													
Product 19	Res1	100	0	0	0	0	0	1400	0	0	7510	0	900	0
	Res2	0	10	0	0	70	0	310	700	7000	14000	700	5500	14000
	Res3	0	0	60	0	0	0	1400	0	7000	0	0	0	0
	Res4	100	50	50	140	60	0	0	0	0	7550	0	400	1000
	total MPS	**200**	**60**	**110**	**140**	**130**	**0**	**3110**	**700**	**14000**	**29060**	**700**	**6800**	**15000**
Product 20	Res1	60	0	50	0	40	0	700	0	0	6000	0	0	0
	Res2	0	0	0	20	0	0	700	0	1000	6000	0	0	0
	Res3	0	0	0	60	0	0	0	0	0	0	400	7000	6000
	Res4	0	40	0	60	0	0	0	300	7000	0	0	0	2000
	total MPS	**60**	**40**	**50**	**140**	**40**	**0**	**1400**	**300**	**8000**	**12000**	**400**	**7000**	**8000**

Results in table4 show that the improvement of achievement level in one objective must be balanced with poor performance on other objectives, which reminds us of the conflicting objectives in the creation of MPS. Figure7 shows the comparison of the fitness values obtained in the three cases considered.ie, with equal weights and that with the two cases (unequal weights). Table 4 gives the final summary of the results obtained from which it can be concluded that the TLBO methodology proposed has outperformed the existing work.

The work showed that master plan created with MOMTLBO presented low levels of ending inventory; low levels of requirements not met and efficiently met safety inventory levels. Also, the results show that TLBO approach gives a better result when compared to the existing work with GA.

Table4. Improvement of performance indicators

Performance Measure	%Improvement over MPS GA		
	EQUAL WEIGHTS	CASE-1	CASE-2
FITNESS	25.16	39.8	37.9
EI (units/hour)	39.75	86.1	47.2
RNM (units/hour)	1.34	82 (decline)	89.6(decline)
BSS (units/hour)	75.4	63.4	74.3

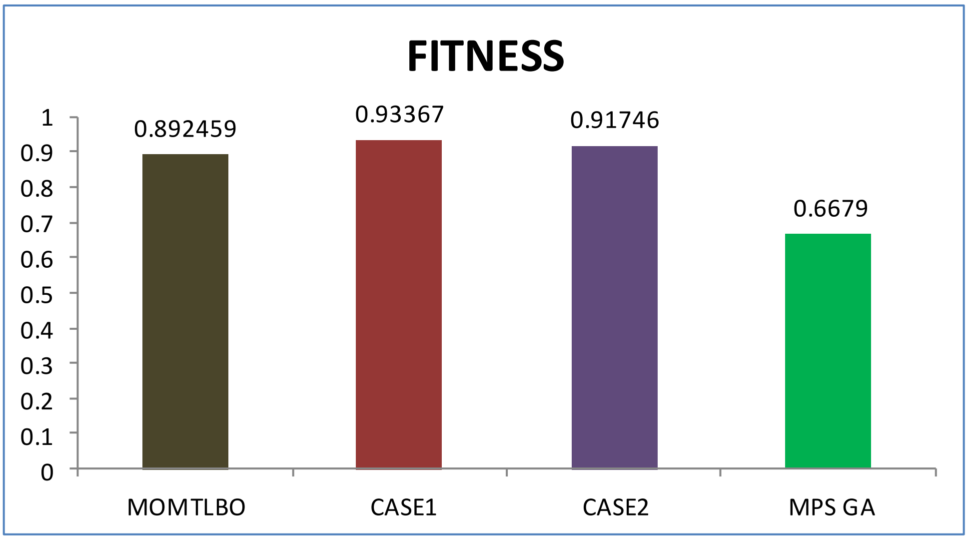


Fig7. Comparison of average fitness values

V. CONCLUSIONS

The complexity of parameter optimization problems increases with the increase in the number of parameters. Even with an increase in number of parameters, the proposed TLBO model is proved to be more advanced and reliable for future research. The results demonstrate that the TLBO method produce more optimal MPS values compared to GA. From the results, one can conclude that, the recently developed TLBO outperforms the rest all algorithms for multi objective optimization MPS problems, with a minimum computational time. Defining more suitable fitness function by considering different weights to the coefficients and their influence may be analysed.

Nomenclature

AC_{rp} = Available capacity, in hours, at the resource is at period p
AIL_{kp} = Average inventory level generated for product k at period p
BI_{kp} = Initial inventory level of the product k at period p
BN_{kpr} = Quantity of standard lot sizes needed for the production of the product k at resource r, at period p
BS_{kp} = Standard lot size for product k at period p
CUH_{rp} = Capacity used from the resource r at period p
CUP_{rp} = Percent rate obtained from the relation of the number of hours consumed from the resource r at the period p, and the available number of hours to the same resource and period
GR_{kp} = Gross requirements for product k at period p
K = Total quantity of different products (SKU)
MPS_{kpr} = Total quantity to be manufactured of the product k at resource r, at period p
$MPST_{kp}$ = Total quantity to be manufactured of the product k at resource r, at period p; (considering all available resources r)
NR_{kp} = Net requirements for product k at period p, considering infinite capacity
OH_k = Initial available inventory (on-hand), at the first scheduling period
P = Total number of planning periods
R = Total quantity of different productive resources
RM_{kp} = Total requirements met for product k at period p
RM_{kpr} = Total requirements met for product k at period p, at resource r
RNM_{kp} = Requirements not met for product k at period p
SL_{kp} = Service level, the relation of the requirements met
SS_{kp} = Safety inventory level for product k at period p
TH = Total planning horizon
TH_p = Available time at each period p
UR_{kr} = Production rate for product k at resource r (units per hour)

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