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Efficient Resources Allocation in Technological Processes Using Genetic Algorithm

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Abstract: One of the main challenges of the automation of complex manufacturing processes is the development of hierarchical control systems. These complex processes have been controlled and managed by individual local subsystems that require mutual coordination. These subsystems might work independently from each other, but pursue a common goal, resulting in a complex global behavior. In this paper, the concept of coordination is understood as the act of making the right allocation of tasks and resources and management actions to meet the objectives of production. An optimization program, based on genetic algorithm, was applied to a dairy plant data; so that this algorithm yielded a set of optimal solutions to maximize profits.

Key words: Distributed objects · Coordination · Resources allocation · Optimization · Genetic algorithm

INTRODUCTION

The modern industrial complexes are a challenge for control engineers, economists, industrial engineers and managers. This complexity arises from the multiple objects spatially distributed over the industrial facilities. These objects might work independently from each other, but pursue a common goal, resulting in a complex global behavior [1]. The autonomous character of these distributed objects DO, in addition to numerous, external or inherent to the process, disturbances lead to a high degree of uncertainty. In this context, the overall efficiency of production lines is a priority. The coordination of the decisions made by the distributed objects is a key factor to more reliable and robust manufacturing systems.

Coordination is the systematic process of analyzing a situation and extracting relevant information [2, 3]. In this paper, the concept of coordination is understood as the act of making the right allocation of tasks and resources and management actions to meet the objectives of production. In a distributed system, multiple objects can have different productivities, efficiencies, objectives and constraints. Therefore, the efficient allocation of resources is often difficult to achieve.

The resources allocation problem has been studied in the literature [4-6]. There are two main approaches for solving RAP: exact methods and approximate methods. The first ensures the optimum solution to the problem, but usually require high computational cost. The second attempts to get families of feasible solutions in a reasonable computation time.

Among the approximate methods, one can find genetic algorithms, [7]. Genetic Algorithms are inspired by the evolution of living beings. Genetic algorithms are inspired by the dynamic mechanical DNA and regulators of biological processes. At the most abstract level, the genetic algorithms are systematic processes to solve problems automatically from a high-level statement of what is expected of the algorithm.

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Table 1:

N	Product	Size	Shell price USD	Cost USD	Demand*	Machine capacity*
1	Pasteurized milk	Liter	0,65	0,59	3651	4000
2	Yogurt	Liter	2,00	1.82	458	500
3	Cheese	750 gr	1,80	1.69	132	150

* Units per day

MATERIALS AND METHODS

For solving problems of multiple distributed objects coordination, it is advisable using the decomposition techniques [8]. These techniques involve the division of complex systems into subsystems of lower order. A set of constraints and parameters corresponds to each subsystem. The objective function of the original system should be established in such a way that it considers all constraints.

The analysis presented here refers to the feasibility study of a dairy plant in [9]. The manufactured products and their economic parameters are listed in Table 1.

The resource to distribute is the unpasteurized milk. The constraints are the demand and the packing capabilities of each line.

The mathematical model is comprised of equations and inequalities 1-5.

$$\textit{Optimization criteria}: \max F_o = \sum_{i=1}^{n} N_i (P_i - C_i) \tag{1}$$

$$\textit{Constraints}: \forall i, \forall r, R_r = \sum_{i=1}^{n} N_i S_i Y_{ir} \tag{2}$$

$$\forall_i, D_i \leq N_i \text{ , } S_i \tag{3}$$

$$\forall l, \forall i, E_i \geq \sum_{i=1}^{n} N_i M_{il} \tag{4}$$

$$\forall i, N_i \geq 0 \wedge N_i \in INT \tag{5}$$

where:

I_i {item 1, item 2, item 3, …, item n}
N_i number of produced item I
S_i Package size of item I
P_i Shell price of milk product type i (\$/unit)
C_i production cost of item I
D_i demand of item I
L_l {line 1, line 2, line 3, …, line l}
E_l efficiency of line l (units/day)
R_r {resource 1, resource 2, …, resource r}
Y_{ir} The amount of resource r require to produce item i

The objective function, equation 1, maximizes the profit generated in the manufacture of the three products. Equation 2 ensures that the amount of milk used in the manufacture of the three products equals the quantity supplied by local farmers. The inequalities 3-5 state that the number of units produced meets demand without exceeding the capacity of the packaging lines.

RESULTS

Figure 1 shows the flow diagram of the system and its subsystems. A computer program was developed to solve the problem of resource allocation. The program is based on the genetic algorithm. At first the program created an initial population. The individuals that took part in the genetic processes were considered according to a fitness function. This function coincides with the objective function of the mathematical model. The offspring, resulted in the genetic processes, must satisfy the requirement of being at least as adaptable as the parents. The algorithm was executed in two ways. First, it was considered that the number of individuals in the population was constant and we varied the number of generation. Then, we considered the number of generations constant and we varied the number of individuals in the population.

In developing of the algorithm, we raised two questions: what is the effect of population size on the optimization result? and what is the effect of the number of generations on the optimization result? To answer the second question we tested the algorithm using the population divergence as the termination criteria. To this purpose we calculated the standard score of the population, Z. When Z was less than a threshold value the algorithm must finish its execution. This first trial led to countless loops. For this reason, we changed to the evolution time termination criterion.

Table 2 and Figure 2 show the results of the program execution when the number of individuals in the population remained constant, n=10 and the number of generations increased each time.

The Table 3 and the Figure 3 show the results, when the number of individuals in the population changed; while the number of generations remained constant.

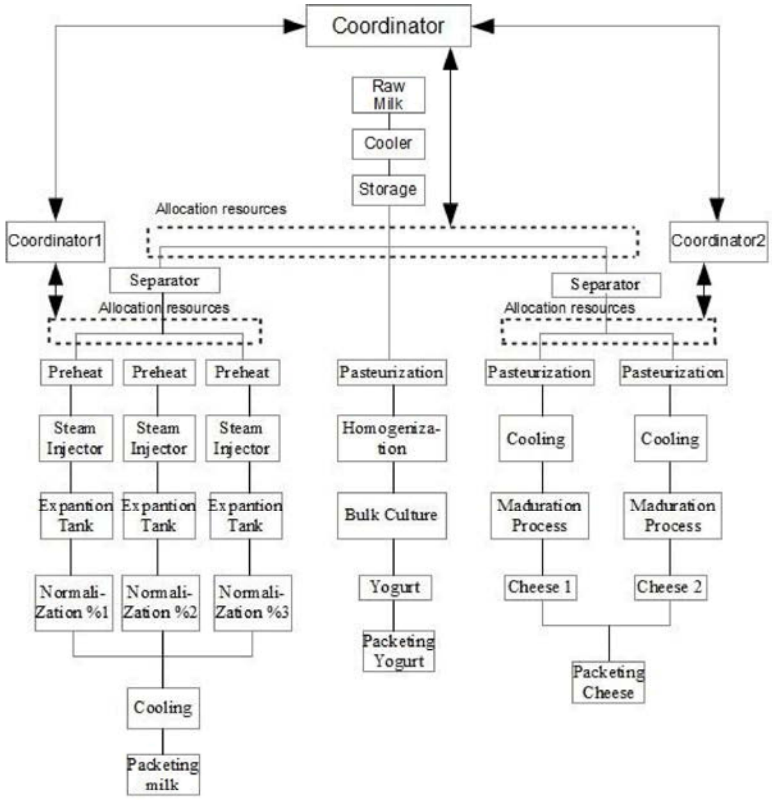

Fig. 1: Flow diagram of the system and subsystems.

Table 2:

			f - objective		
Number	Population size	Generations	Max value	Min value	Coefficient of variation
1	10	5	342,90	323,90	0,3322
2	10	550	335,30	316,70	0,3324
3	10	1100	339,50	319,10	0,3326
4	10	1650	338,70	324,90	0,3321
5	10	2200	343,30	319,90	0,3326
6	10	2750	338,60	323,80	0,3323
7	10	3300	342,80	321,00	0,3329
8	10	3850	343,40	320,90	0,3326
9	10	4400	341,90	325,40	0,3321
10	10	4950	341,20	321,10	0,3324

Table 3:

			f - objective		
Number	Population size	Generations	Max value	Min value	Coefficient of variation
1	5	10	330,40	319,00	0,4902
2	550	10	344,30	294,60	0,0539
3	1100	10	344,70	294,80	0,0343
4	1650	10	345,00	296,20	0,0417
5	2200	10	344,30	294,20	0,0408
6	2750	10	344,40	294,40	0,0386
7	3300	10	345,10	295,00	0,0394
8	3850	10	344,70	294,90	0,0379
9	4400	10	344,40	295,10	0,0368
10	4950	10	344,80	294,30	0,0373

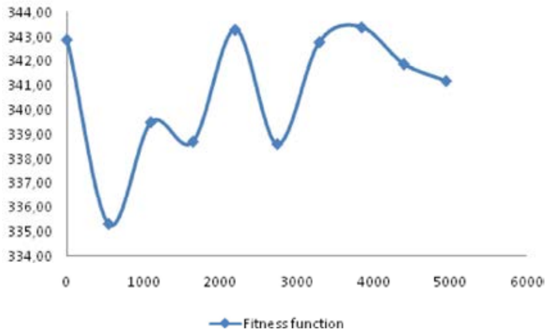

Fig. 2: Effects of number of generations on fitness function

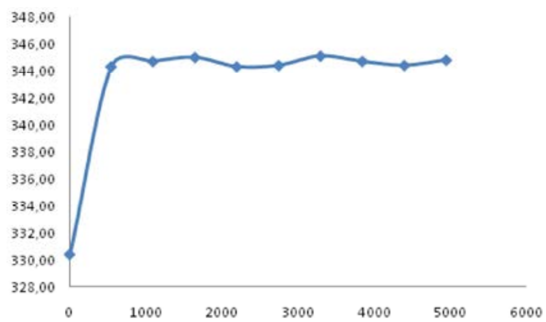

Fig. 3: Effects of population size on fitness function

In the first case, we see that the fitness function did not converge to a steady value. For a population of ten individuals, the coefficient of variation keeps unchanged even for a large number of generations. In the second case, there is a rapid convergence of the values of the fitness function f and a rapid decrease of the coefficient of variation. However, for populations of more than 3000 individuals, the run time was larger.

CONCLUSION

We have written a program based on a genetic algorithm for distributed object coordination. The coordination aspect studied here is the allocation of resources. In this work, we found that the number individuals in the population are a key factor in the performance of the algorithm. For this point, it becomes indispensable to run cycles of tests to determine the optimal ratio between the number of individuals, the number of generations, the runtime and the convergence of the fitness function. The program was applied to the optimization of a dairy plant where they manufacture only 3 products. It was taken only one resource to be allocated among packaging lines. For practical purposes it would be of interest to extend this analysis to situations where there are more resources to be distributed.

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