Journal of Industrial and Systems Engineering
Vol. 9, No. 2, pp 54-66
Spring (April) 2016

Impact of queuing theory and alternative process routings on machine busy time in a dynamic cellular manufacturing system

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Abstract

A new mathematical model based on the alternative process routings in presence of a queuing system in a dynamic cellular manufacturing system has been proposed in this paper. This model integrates two problems of cell formation and inter-cell layout and also an efficiency factor which is defined for minimizing the cell load variation through the maximizing the busy time for all machine types. In order to evaluate the performance of proposed model, some numerical examples are generated randomly and solved using GAMS optimization software suitable for MIP and MINLP models. The Baron solver which is capable of solving both linear and nonlinear model is implemented. Experimental results verify the applicability of proposed model in every industrial plant which implements a CMS. Moreover, based on the sensitivity analysis, the queue system has significant impact on overall system efficiency. In other words by increasing the part arrival rate the machine busy time is increased strictly.

Keywords: Queuing theory, Cellular Manufacturing System, Machine breakdown, reliability.

1- Introduction

Cellular ManufacturingSystem (CMS) is a practical tool of Group Technology (GT) philosophy which aims at improving the total efficiency of the production system. In today's competitive environment it is necessary to have an efficient manufacturing system with the high amount of flexibility in coping with the erratic nature of the real world elements such as part demand and diversification. A CMS designing problem includes four sub problems which should be solved sequentially or concurrently. These sub

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ISSN: 1735-8272,

problems are Cell Formation (CF), Group Layout (GL), Group Scheduling (GS) and operator assignment problems. In developing countries like Iran managersusually like to continue the manufacturing with traditional systems. The implementation of CMS needs to change a manager's insight to the modern world requirements. If these scientific researches would be supported by both the university and industry they can be applied and used in real word manufacturing companies. More sensitivity analyses required to suffice managers that the proposed system is stable and reliable.

Solving the CF problem is the first stage which should be regarded basically during the optimization process. So in recent years many analytical approaches like mathematical programming, heuristic solution procedures, meta-heuristics, clustering and graph theory based theoriesare investigated by many researchers. Recently,Dalfard (2013) has developed a new nonlinear mathematical model to solve the dynamic CF problem which takes in to account the number and average length of inter-intra cell trips associated with a Simulated Annealing (SA) meta-heuristic embedded in branch and cut process to solve the problem more efficiently. Ilić (2014) proposed an e-learning based algorithm to solve the CF problem optimally. Three types of initial machine-part matrix including binary (zero-one), production volume and operation time matrixes are regarded. Bagheri & Bashiri (2014a)developed a hybrid Genetic Algorithm (GA) and Imperialist Competitive Algorithm (ICA) to solve a CF problem. Reza Tavakkoli-Moghaddam et al. (2012)proposed a scatter search algorithm to solve the CF problem with respect to the four objectives including minimization of total fixed-variable cost, intercellular part trips cost and cell load variation and also maximization of machine utilization factor. Arani, S. D., and Mehrabad, M. S. (2014) have employed Automated Guided Vehicles (AGVs) to transfer the jobs which may need to visit one or more cells. Tavakoli-Moghadam et al. (2006)have developed a model for facility layout problem in CMS with stochastic demands. The main goal of objective function is to minimize inter-cell and intra-cell part trips. Moreover; a comprehensive mathematical model has been proposed by R Tavakkoli-Moghaddam et al. (2008). The fuzziness and uncertainty concepts have been studied in their research, where its objectives are minimization of total machines and parts costs, maximization of preference level of the decision making (DM) and balancing the intracellular workload. Niakan et al. (2015) have examined a new multi-objective mathematical model in a Dynamic Cell Formation Problem, where social criteria and uncertainty conditions are considered. Furthermore, Chung et al. (2011)have developed an effective Tabu Search (TS) algorithm to solve the CF problem. Moreover; machine reliability and alternative process routings are considered in their research. Besides the mentioned studies there are many other studies in which the optimization of the CF problem has been studied. For exampleDefersha & Chen (2006; Elbenani et al. (2012; Saraç & Ozcelik (2012).

Integration of the CFP with GL problem is a new practical concern which has attracted the attention of many related practitioners to propose some new optimization tools in recent years. Although the inter cell layout problem basically is about the cell's locations, the intra cell layout problem is related to the determining the position of a machine within a cell. Totally these two problems are knows as a Group Layout problem. Because of complexity of given problems, most of these studies have considered the GL problem as a sequel to the CF problem. Ulutas (2015) has presented a Clonal Selection Algorithm (CSA) to solve a classical CFP that outperforms current available heuristics in the literature. Bashiri & Bagheri (2013)proposed a two stage heuristic clustering based approach to solve a CFP problem associated with the operator assignment problems. In their research the CFP solution obtained by a clustering technique is an input as a candidate solution for a mathematical programming problem. Wu et al. (2007)developed a GA approach to solve these two problems associated with the GS problem. Arkat et al. (2012) proposed a new mathematical model which solves the CF and GL problems simultaneously. Then the model was extended by incorporating the GS problem in designed framework which has significant impact on total system efficiency. Reza Tavakkoli-Moghaddam et al. (2007) have considered a predefined CF structure as an input for the GL problem. In their proposed mathematical model, demand is regarded as a stochastic parameter. Also Bagheri & Bashiri (2014b)developed a comprehensive mathematical model which integrates the CFP with inter-cell GL and also operation assignment problems. In their research it has been shown that these problems are interrelated and must be solved concurrently in order to find an optimal solution for the total system.

Proposing new mathematical programming models in which the practical aspects of a cellular environment are taken into account should be a useful research especially for those who want to design an efficient manufacturing system. There are many researches in literature in which the uncertainty of the manufacturing system like stochastic nature of part demand and production mix has been regarded. However, almost the parts arriving rate in a CMS environment is not considered as a major factor which has a significant impact on machine busy time. In this paper machine utilization factor is investigatedin presence of uncertainty in parts arrival rate and mean number of parts processed by machines. Ghezavati & Saidi-Mehrabad (2011)proposed an efficient hybrid self-learning method to solve the CFP. This paper is extension of their work by incorporating some other real world production elements like machine busy time and dynamic alternative process routings associated with the inter-cell layout determination. In a queue system, the customers (parts) have a stochastic arriving rate and wait in a queue to be served by an available server (machine). Two kinds of arriving patterns can be considered: Number of arrivals in a time interval follows a probability distribution or this value is determined by the mean number of parts processed by a machine based on its processing time. Figure1 illustrates the concept of a queue system in the CMS environment. Three different concepts are defined during this research: first is the Machine Utilization Factor (MUF) which can be calculated for a specific part by this part mean number of arrivals divided by the mean number of total parts which should be processed on the corresponded machine. The second is the Total Machine Utilization Factor (TMUF) which is the sum of MUF for all parts processed by this machine. The third concept implemented in this paper is the Efficiency Factor (EF) which is the sum of TMUF value for all machines. The TMUF must be less than 1 so that the queue system will remain in a stable mode. Hence the number of arrivals should be less than the number of processed parts on the specific machine. The alternative process routing controls this rational theory. In this paper a new mathematical model has been developed in order to design an efficient CMS in which the maximum EF is obtained through the optimal selection of the alternative process routings. The main objectives of proposed mathematical model are to minimize the intra cell art trips, system reconfiguration cost and also maximization of the system EF value.

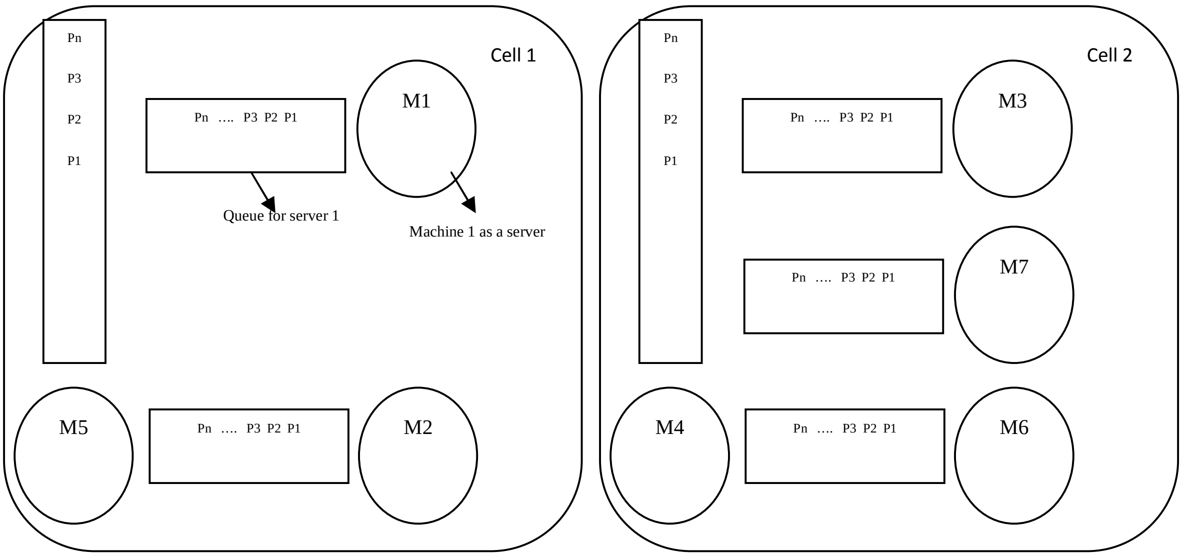

Fig 1. The schematic view of the part queuing in CMS

The rest of this paper is organized as follows: In next section, a new linear MIP programming model is described which is the transformation of the preliminary explained nonlinear mathematical model based on mentioned objectives. In section 3, the proposed model efficiency will be verified by some hypothetical numerical examples followed by conclusion and future directions in section 4.

2- The proposed mathematical model

2-1- Model description

As mentioned previously the EF is considered as a main factor in a CMS to enhance the efficiency of a practical manufacturing system. The machine total utilization factor (EF) or the probability that machine *j* in production *h*, is busy can be determined by equation 1.

$$\rho_i^h = \frac{\sum_{j=1, j\in A}^{J} \lambda_{jh}}{\mu_i^h} \quad \forall i, h \tag{1}$$

In equation 1 *A* is the set of different parts which are planned to be processed by machine *i*, λ_{jh} is the mean number of arriving parts per unit time and μ_i^h is the processing rate of machine *i* which is the mean number of different parts processed by machine *i* in production *h*. The introduced efficiency factor for production period *h*can be obtained by equation 2.

$$EF_h = \sum_{i=1}^{I} \rho_i^h \quad \forall h \tag{2}$$

There are some assumptions which are required in order to simplify the problem. In this paper it is assumed that some elements like part demand, number of cells and their upper-lower bounds are predefined and constant during the production horizon. There is some alternative process routings for some parts which the best one should be selected based on the model objectives. The intra cell part trip is based on the number of trips and the distances between the machines are not important. However, the system reconfiguration cost is based on the distances between the cells which should be located in predefined cell locations. These candidate locations are predetermined and constant over the production horizon.

2-2- Notation

Sets

I	Number of machines
J	Number of parts
C	Number of machine cells which should be constructed
G	Number of candidate locations to be a cell ($G \geq C$)
H	Number of production periods

L_j^h Number of process routings for part type j in period h.

Indices

i, i' Machine index

j Part index

c, c' Cell index

h Production period index

g, g' Location index

l Routing index

U_{lj}^i Index for machines existed in routing l of part type j.

Parameters

W_i The importance weights for intra cell part trips, system reconfiguration cost and also efficiency factor

A_1 Unit cost of an intra cell part trip

γ_i System reconfiguration cost for machine i including machine uninstall, install, and movement costs.

D_j^h Demand value for part j in period h

$dis_{gg'}$ Distances between two candidate locations

g and g'

λ_{jh} Arriving rate for part type j, in production period h

μ_i^h Mean number of different parts processed by machine i in period h

t_{ji} Processing time for part type j on machine type i

u_c, l_c The upper and lower machine capacity for cell c

Decision variables:

$$X_{ic}^h = \begin{cases} 1; & \text{If machine } i \text{ is assigned to cell } c \text{ in period } h \\ 0; & Otherwise \end{cases}$$

$$Y_{cg}^{h} = \begin{cases} 1; & \text{If cell } c \text{ is located in location } g \text{ in period } h \\ 0; & Otherwise \end{cases}$$

$$Z_{lj}^{h} = \begin{cases} 1; & \text{If routing l of part j should be selected in period h.} \\ 0; & \text{Otherwise} \end{cases}$$

ρ_i^h Machine i total utilization factor in production h

2-3- Objective function and constraints

The mixed integer nonlinear mathematical model for the CMS design is presented as follows:

$$\min \quad objective\ function =$$

(3a)

$$W_1 [\sum_{h=1}^{H} \sum_{j=1}^{J} \sum_{l=1}^{L_j} \sum_{i=1}^{K_{lj}-1} \sum_{c=1}^{C} A_1 Z_{lj}^{h} D_j^{h} \max(X_{(U_{lj}^{i})c}^{h} + X_{(U_{lj}^{i+1})c}^{h} - 1, 0)]$$

$$+W_2 [\sum_{h=1}^{H-1} \sum_{i=1}^{I} \sum_{c=1}^{C} \sum_{c'=1}^{C} \sum_{g=1}^{G} \sum_{g'}^{G} \gamma_i Dis_{gg'} \times \max(X_{ic}^{h} Y_{cg}^{h} + X_{ic'}^{h+1} Y_{c'g'}^{h+1} - 1, 0)] \quad (3b)$$

$$-W_3 [\sum_{h=1}^{H} EF_h] \quad (3c)$$

Subject to:

$$\sum_{c=1}^{C} X_{ic}^{h} = 1 \quad \forall i, h; \quad (4)$$

$$\sum_{i=1}^{I} X_{ic}^{h} \le u_c \quad \forall c, h; \quad (5)$$

$$\sum_{i=1}^{I} X_{ic}^{h} \ge L_c \quad \forall c, h; \quad (6)$$

$$\sum_{g=1}^{G} Y_{cg}^{h} = 1 \quad \forall h, c; \quad (7)$$

$$\sum_{c=1}^{C} Y_{cg}^{h} \le 1 \quad \forall h, g; \quad (8)$$

$$\sum_{l=1}^{L_j} Z_{lj}^{h} = 1 \quad \forall j, h \tag{9}$$

$$\rho_i^h = \frac{\sum_{j=1}^{J}\sum_{l=1}^{L_j} Z_{lj}^{h} \lambda'_{jh}}{\mu_{(U_{lj}^{i})}^{h}} \quad \forall i, h \tag{10}$$

$$0 \le \rho < 1$$

$$Z, X, Y \in \{0,1\} \tag{11}$$

Objective function of the proposed model includes 3 different terms. The first term, i.e. (3a), is to minimize the intra-cell part trips. It shouldbe noted that an intra-cell part trip is determined irrespective of machine locations inside the cells. Term (3b) is to minimize the system reconfiguration cost over the production horizon. This term is because of thedynamic nature of a cellular system. In other words parts demands erratic nature and differences of production mix in each production period force the system to change the layout. This cost includes uninstalling, movement and installing the machines between the cells based on inter- cell layout distances. Term (3c) is to maximize the efficiency factor introduced in this paper. Maximizing a machine busy time will lead to the cell load variation minimization indirectly by choosing an optimal routing for each part type. Eq. (4) implies that each machine type must be assigned to a cell. Constraints (5) and (6) ensure that the number of machines for a cell is not exceeded lower and upper bounds of that cell size. Eq. (7) implies that each cell must be established in a candidate location. Furthermore, in a candidate location only one cell can be established. This issue is considered by constraint (8). Constraint (9) indicates that just a single process routing will be selected as an optimal route for each part. Eq. (10) is revised form of equation (1) which calculates the TMUF based on selected routing for a part type. As stated before this value should be maximized by selecting an optimal routing for each part type. Finally constraint (11) defines the variables types.

2-4- Transformation to a linear model

Terms (3a) and (3b) in the objective function are nonlinear. Since thelinear models are less complicated than nonlinear models from computational time view point the proposed model can be reformulated as a pure 0-1 linear programming model by introducing some new variables with auxiliary constraints which will lead to solving the problem in a less computational time. The linearization procedure implemented in this paper consists of two steps which can be described as follows: term (3b) has two kinds of nonlinearity. It contains the multiplication of two binary variables. So a new variable of XY_{icg}^{h} can be defined which is replaced as:

$$XY_{icg}^{h} = X_{ic}^{h} Y_{cg}^{h} \quad \forall i, c, g, h;$$

So the following constraints should be added to the proposed mathematical model:

$$XY_{icg}^{h} \le X_{ic}^{h} \quad \forall i, c, g, t \tag{12}$$

$$XY_{icg}^{h} \le Y_{cg}^{h} \quad \forall i, c, g, h; \tag{13}$$

$$XY_{icg}^{h} \ge X_{ic}^{h} + Y_{cg}^{h} - 1 \quad \forall i, c, g, h; \tag{14}$$

The second nonlinearity in both terms (3a) and (3b) is related to the “Max” function. Defining new binary variables as $N_{(U_{lj}^{i})c}^{h}$, $E_{icc'gg'}^{h}$ which are replaced by following equations:

$$N^{h}_{(U^{i}_{lj})(U^{i+1}_{lj})c} = \max(X^{h}_{(U^{i}_{lj})c} + X^{h}_{(U^{i+1}_{lj})c} - 1, 0)$$
$$\forall l, i, j, c, h;$$
$$E^{h}_{icc'gg'} = \max(XY^{h}_{icg} + XY^{h+1}_{ic'g'} - 1, 0)$$
$$\forall i, c, c', g, g', h;$$

Six auxiliary constraints should be added to the proposed model as follows:

$$N^{h}_{(U^{i}_{lj})(U^{i+1}_{lj})c} \geq X^{h}_{(U^{i}_{lj})c} + X^{h}_{(U^{i+1}_{lj})c} - 1 \quad (15)$$
$$\forall l, i, j, c, h;$$
$$N^{h}_{(U^{i}_{lj})(U^{i+1}_{lj})c} \geq 0 \quad \forall l, i, j, c, h; \quad (16)$$
$$E^{h}_{icc'gg'} \geq XY^{h}_{icg} + XY^{h+1}_{ic'g'} - 1 \quad (17)$$
$$\forall i, c, c', g, g', h;$$
$$E^{h}_{icc'gg'} \geq 0 \quad \forall i, c, c', g, g', h; \quad (18)$$

Accordingly the final linear mathematical model can be presented as follows:

$$\min \quad objective\ function =$$
$$W_1[\sum_{h=1}^{H}\sum_{j=1}^{J}\sum_{l=1}^{L_j}\sum_{i=1}^{K_{lj}-1}\sum_{c=1}^{C} A_1 D^{h}_{j} ZN^{h}_{(U^{i}_{lj})(U^{i+1}_{lj})c}] \quad (3d)$$
$$+W_2[\sum_{h=1}^{H-1}\sum_{i=1}^{I}\sum_{c=1}^{C}\sum_{c'=1}^{C}\sum_{g=1}^{G}\sum_{g'}^{G} \gamma_i Dis_{gg'} E^{h}_{icc'gg'}] \quad (3e)$$
$$-W_3[\sum_{h=1}^{H} EF^{h}] \quad (5e)$$

Subject to:

Unaltered set constraints (4) – (11), and new auxiliary constraints (12) – (18).

The last set constraint, i.e. (11), is replaced by:

$$Z, X, Y, XY, E \in \{0,1\}$$
$$0 \leq \rho < 1 \quad (19)$$

3- Numerical examples

In order to evaluate the applicability of the proposed mathematical model, some numerical examples are generated randomly and solved using GAMS optimization software of 23.5-Cplex on a Core i5 PC with 1 GB RAM. The numerical examples general information and obtained results are reported in table 1. This table also shows the comparison between two linear and non linear models from computational time aspect. According to table 1 linear model can find the optimal solution in less computation time than nonlinear model. The optimal solutions are found using Cplex and Baron Solvers for linear and nonlinear models respectively.

Table 1. Experimental results of proposed numerical examples

Example number	**Problem size:** **Number of parts- Number of machines- Number of cells - Number of locations- Total available routes**	**Objective value-Computation time(s) forMIP model**	**Objective value-Computation time(s) forMINLPmodel**
1	3- 3- 2-3-6	5.65-0.58	5.65-0.9
2	4- 5- 3-5-6	34-0.53	34-0.89
3	4- 7- 4-6-8	6.3-2.6	6.3->1800

To analyze the proposed mathematical model in more details, input information of the last example (i.e., example 3) is reported in tables 2-4. These tables include part- machine information, machine related information and the candidate locations distances, respectively. Minimum and maximum machine capacities for each cell are 1 and 3, respectively ($L_c = 1, U_c = 3$).Optimal cell formation and routings obtained for this example are reported in tables 5-6. According to table 6 the machine type 4 has the maximum EF value of 0.9 in period 1. Based on the alternative process routings depicted in table 2 this machine should be used for both parts 1 and 2. Moreover, since the operating cost and the processing time of this machine is low in comparison to the other machines the second routing in which machine 4 is active has been selected. So its busy time is calculated as 0.9. As it was predictable, the parts arrival rate (queuing system) has significant impact on overall system efficiency.

Table 2. The input information of part-machine matrix – example 3

Period 1					
Parts	**Routes**	**Process sequence**	**Processing time for each operation**	**Demand** (D_j^1)	λ'
1	Rout1	2-3-4-5-7	0.7, 0.3, 0.5, 0.2, 0.5	20	3
2	Rout 1	4-5-2-7-3-6-1	0.05, 0.1, 0.1, 0.5, 0.3, 0.3, 0.3, 0.1	100	3
3	Rout 1	4-6-7-2-5-2	0.6, 0.6, 0.2, 0.2, 0.1, 0.2	20	3
	Rout 2	3-1	0.7, 0.9		
4	Rout 1	6-2-1-3	0.5, 0.1, 0.2, 0.6	100	3
	Rout 2	6-4-5	0.5, 0.6, 0.5		
Period 2					
Parts	**Routes**	**Process sequence**	**Processing time for each operation**	**Demand** (D_j^1)	λ'
1	Rout 1	2-3-2	0.7, 0.3, 0.7	20	3
	Rout 2	4-1-5-3	0.1,0.5, 0.3, 0.3		
2	Rout 1	4-3-2-3-2	0.4, 0.2, 0.3, 0.2, 0.3	50	3
	Rout 2	7-6-1	0.2,0.7,0.1		
3	Rout 1	5-4-3-1	0.5, 0.5, 0.3, 0.05	100	3
	Rout 2	1-3-5-4-7	0.05, 0.3, 0.5, 0.5, 0.2		
4	Rout 1	4-5-6-5-7	0.3, 0.2, 0.5, 0.2, 0.5	80	3
	Rout 2	4-5-6-3-2	0.3, 0.2, 0.5, 0.6,0.1		

Table 3. The machine related information – example 3

Machine type	**Service rate (** μ_i **)**	**Relocation cost (** γ_i **)**
1	20	1
2	15	3
3	20	4
4	10	5
5	16	6
6	16	7
7	15	10

Table 4. Distance of cell locations to each other– example 4

Location	1	2	3	4	5	6
1	0	5	7	7	6	5
2	5	0	2	5	5	4
3	7	2	0	3	4	3
4	7	5	3	0	8	2
5	6	5	4	8	0	1
6	5	4	3	2	1	0

Table 5. Optimal routings obtained for different part types- example 3

Part type	1	2	3	4
Optimal APR (period 1)	1	1	1	1
Optimal APR (period 2)	1	1	2	2

Table 6. Optimal cell formation and EF value for different machines- example 3

Machine type	Machine efficiency factor in both periods	Cell in which the machine is installed in both periods
1	0.3,0.3	4,2
2	0.4,0.4	2,1
3	0.45, 0.3	1, 4
4	0.9, 0.6	4, 2
5	0.562, 0.562	1, 4
6	0.375, 0.375	2,1
7	0. 4, 0.4	3,3

4- Conclusion

This paper presented a mathematical model for dynamic cellular manufacturing system based on queuing theory. The objectives were minimization of intra-cell part rips, system reconfiguration cost and also maximization of total efficiency factor which is equal to all machines busy time probability. Experimental results verified the efficiency of proposed model in both optimality and computational time aspects. Also based on sensitivity analysis of the presented model, it can be inferred that part arrival rate has the significant impact in process routing selection which in turn affects the machine utilization factor. However; this study is still open for incorporating other features in future researches. Some guidelines for future studies can be outlined as follows:

Solving the proposed model for large size examples is computationally intractable. So, proposing new heuristic and meta-heuristics to solve the model for large size problems, optimally could be suggested.

Incorporating new real world production factors such as production planning concept and intra cell layout problem can be studied in provided framework.

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