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Decision Rules for the Robotic Mobile Fulfillment System of A PCB Assembly Factory Warehouse

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Introduction

Surface mount technology (SMT) becomes an important method in PCB assembly. For a production order, operators manually pick the required components rely on the paper-based document of the PCB BOM by walking in the warehouse. This pickers-to-goods operation takes long time to pick the required components for a production order and could yield picking error and more time spent reviewing the picking order.

Robotic mobile fulfillment system (RMFS) is a popular goods-to-pickers system for e-commerce fulfillment center in recent years. To the best of our knowledge, there is limited RMFS application in factory warehouse. The case company does not really know the decision rules used in the system. This research will collect data from the warehouse and construct a simulation model and evaluate different decision rules for interdependent sub-problems.

We consider four interdependent operational problems: pick order selection (POS), pick pod selection (PPS), pick bot selection (PBS), and pod storage assignment (PSA).

Objectives

- Define the decision rules of the studied operational problems in RMFS
- Observe and collect data from the current RMFS
- Construct the simulation model of the RMFS based on RAWSim-O
- Analyze the performance for different rule configurations
- Provide good rule configurations

Methodology

The open source simulation model RAWSim-O developed by Merschformann et al. (2018) is adapted and new functions are added for the designed rules in this research. The decision rules for each problem are listed in table 1. 96 rule configurations are tested and compared.

Table 1. Decision rules for each operational problem

Decision Problems	Proposed Rules
Pick Order Selection (POS)	0: Random (POS-R)
	1: Largest Quantity (POS-H)
	2: Index Number (POS-I)
	3: Pod-Match (POS-P)
Pick Pod Selection (PPS)	0: Random (PPS-R)
	1: Nearest (PPS-N)
	2: Largest Components Qty (PPS-C)
	3: Largest Reels Qty (PPS-Q)
Pick Bot Selection (PBS)	0: Random (PBS-R)
	1: Nearest (PBS-N)
Pod Storage Assignment (PSA)	0: Random (PBS-R)
	1: Nearest (PBS-N)
	2: Fixed (PBS-F)

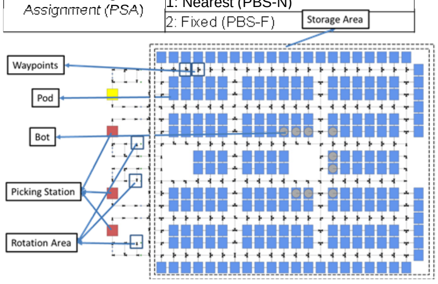

Figure 1. Factory warehouse layout

Assumptions:

1. AGV breakdown does not occur and battery charged in not considered.
2. The FAR path planning is used.
3. There are up to 9 AGVs used in the system.
4. At most three picking stations can be used.
5. Picking time is collected from the real data (constant).
6. The reel selected from the pod is based on the rule.

Table 2 presents the parameter settings in the simulation model. There are 216 pods stored in the warehouse. Figure 1 shows the factory warehouse layout of the case company.

Table 2. Parameter settings

Object	Parameter	Value
Pod	Capacity	2880 Reels
	Slot per pod	144 Slots
	Reel per slot	20 reels
Robot	Acceleration/deceleration	2 M/Sec^2
	Top Speed	2 M/Sec
	Loading pod time	3 Sec
	Unloading pod time	3 Sec
	Rotating pod times	3 Sec/360^0
Station	Picking time	15 Sec/reel
	Maximum Queueing Bots	5 Bots/station

Results

Two collected orders are simulated (140 SKUs/257,629 components and 143 SKUs/774,417 components). We compare eight key performance indicators: makespan (MS) in seconds, bot traveling distance (BDT) in meters, bot utilization (UT), station utilization (ST), number of pod trips (PT), number of reel handled (RH), Pile-on (PO), and inventory reduction (IR) in percentage. Table 3 shows the results for the first order simulation. POS-I achieves the smallest makespan, while POS-P provides the largest inventory reduction (# of reels handled). The pod order selection and pick pod selection problems affect the makespan and inventory reduction as shown in table 4.

Table 5 presents the results for the larger assembly order simulation. In this order, PPS-C yields the smallest makespan, and POS-P has the largest inventory reduction (# of reels handled). Figure 2 shows the number of reels handled for different decision rules. We further analyze the multiple factor ANOVA on the makespan for different rules of operational problems. Figure 3 presents interaction of two operational problems on the makespan. Only POS and PPS show the difference among different rule combinations. The POS-I and PPS-C rule combination provides the smallest makespan.

Table 3. Results of different decision rules on first order

Rule	MS (Sec)	BDT (m)	BU %	SU %	PT	RH	PO	IR %
POS-R	4305.8	4540.1	70.1	91.5	70.5	263.5	3.7	6.1
POS-H	3975.6	4519.0	70.4	90.9	70.4	241.6	3.4	5.5
POS-I	**3803.5**	4393.2	70.3	90.9	67.9	230.6	3.4	5.3
POS-P	6840.8	**3513.6**	67.4	95.7	53.6	**436.2**	**8.2**	**10.0**
PPS-R	5077.9	4511.1	69.4	92.9	66.0	315.8	5.0	7.2
PPS-N	4715.3	4004.7	69.5	92.1	68.9	291.4	4.5	6.7
PPS-C	3974.0	4131.3	70.1	90.8	61.2	243.7	4.2	5.6
PPS-Q	5158.5	4318.9	69.2	93.0	66.2	321.2	5.0	7.4
PBS-R	4736.2	4255.0	69.5	92.2	65.7	293.2	4.7	6.7
PBS-N	4726.7	4228.0	69.7	92.3	65.5	292.9	4.7	6.7
PSA-R	4735.2	4230.5	69.6	92.4	65.4	293.6	4.7	6.7
PSA-N	4752.9	4232.6	69.4	92.1	65.7	294.1	4.7	6.8
PSA-F	4706.3	4261.4	69.6	92.2	65.6	291.4	4.7	6.7

Table 4. ANOVA of KPIs on first order

Rule	MS	BDT	PT	RH	IR
POS	0.000*	0.000	0.000	0.000	0.000
PPS	0.000	0.000	0.000	0.000	0.000
PBS	0.915	0.448	0.653	0.960	0.960
PSA	0.912	0.731	0.919	0.926	0.926

Table 5. Results of different decision rules on second order

Rule	MS	BDT	BU	SU	PT	RH	PO	IR
POS-R	6011.7	5356.5	69.1	93.1	88.3	373.6	4.2	1.0
POS-H	5999.3	5692.8	69.5	92.5	93.5	371.5	3.9	1.0
POS-I	6077.7	6064.5	70.0	91.6	103.3	374.7	3.9	1.0
POS-P	9481.1	**4063.0**	66.9	96.6	64.5	**610.6**	**9.5**	**1.7**
PPS-R	7031.4	6116.9	69.3	93.4	94.5	440.1	5.2	1.2
PPS-N	6890.1	5215.6	69.1	93.3	96.9	430.6	5.1	1.2
PPS-C	**5011.9**	4496.2	69.1	92.0	68.5	312.1	4.7	0.9
PPS-Q	8636.2	5348.1	**68.0**	95.0	89.6	547.6	6.5	1.5
PBS-R	6893.7	5456.3	68.9	93.5	87.5	432.7	5.4	1.2
PBS-N	6891.2	5132.1	68.9	93.4	87.3	432.5	5.4	1.2
PSA-R	6894.7	5313.8	68.9	93.5	87.6	433.1	5.4	1.2
PSA-N	6895.6	5240.0	68.8	93.3	87.2	432.4	5.4	1.2
PSA-F	6887.0	5328.8	68.9	93.5	87.4	432.3	5.4	1.2

Table 6. ANOVA of KPIs on second order

Rule	MS	BDT	PT	RH	IR
POS	0.000*	0.000	0.000	0.000	0.000
PPS	0.000	0.000	0.000	0.000	0.000
PBS	0.986	0.000	0.888	0.985	0.985
PSA	0.999	0.632	0.982	0.997	0.997

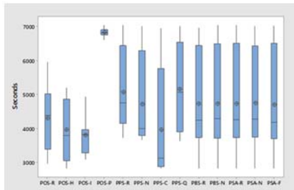

Figure 2 Boxplot of number of reels handled

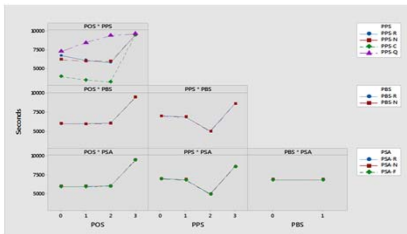

Figure 3 Multi factor ANOVA on makespan

Conclusions

- Decision rules in Pick pod selection and pick order selection significantly affect the makespan and inventory reduction.
- The largest component quantity in pick pod selection problem can achieve the smallest makespan, while largest quantity in pick order selection and largest reel quantity in pick pod selection will provide the largest inventory reduction.
- Number of bots and picking stations will affect the KPIs. For a single picking station, increase the number of AGVs in the system cannot reduce the makespan.

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