GENERIC SIMULATION MODEL FOR ASSEMBLY LINE SUPPLY

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ABSTRACT

In this paper a simulation model for materials supply to mixed-model assembly lines is discussed. The model is created in FlexSim and demonstrates the in-plant logistical flows involved to supply parts from the warehouse to the use-points at the assembly line. The materials supply methods shown are bulk feeding (also referred to as line stocking) and kitting. The results of the simulation model are compared to the results of a deterministic mathematical cost model to study the impact of real production variations and dynamics. Testing is done based on a case study where 438 parts are supplied to 23 work stations o of which 146 are supplied in bulk, while the remaining parts are kitted. To create this specific model an automatic model generator is used. The findings of this study are reported.

INTRODUCTION

To have efficient assembly processes, the right parts need to be provided close to the use-points at the line at the right time. Different ways exist to supply parts to an assembly line. It can go from bulk feeding, where original supplier containers are transported to the line without any additional material handling, to kitting, where materials are already grouped in kit containers per end product before transport to the line takes place. Other line feeding methods exist which tend to be intermediate forms between bulk feeding and kitting.

Weighing the pros and cons of different line feeding methods is not an easy task and intuitive knowledge about the different systems is not enough to choose the best and most cost-effective solution. Therefore a mathematical model (Limère 2011, Limère et al. 2012) has been developed to guide the decision when choosing between bulk feeding and kitting. Limère et al. (2012) modeled the problem as a static and deterministic optimization model and take as such no stochastic effects into account. For this reason, a simulation model is now built to check if any stochastic effects would

have an impact on the cost calculations and the optimal solution of the mathematical model.

LITERATURE REVIEW

In 2010, Hua and Johnson identified a number of research issues concerning the choice of kitting versus line stocking (Hua and Johnson, 2010). They confirmed that research on this topic has been sparse, and suggested further research to the impact of product and component characteristics on the choice to kit or not to kit. Before 2010, one important publication had already studied some of these aspects. Bozer and McGinnis (1992) developed a descriptive model for decision making. Multiple criteria were studied and thus facilitated a quantitative comparison between various kitting plans and line stocking.

To obtain an optimal decision for every part, Caputo and Pelagagge (2011) studied some hybrid policies based on an ABC classification. For each of the three classes A, B and C, a choice could be made between kitting, Kanban-JIT and line stocking. The different scenarios proposed are analyzed for a case study and multiple performance measures are given to compare the solutions and choose the most preferred one. This means that the different performance measures still will have to be weighted according to one's preference, before a solution can be selected.

Hanson and Brolin (2013) compare kitting and bulk feeding based on two case studies. After a detailed analysis of the case studies they give an overview of some comparisons between both systems according to four categories, namely man-hour consumption, product quality and assembly support, flexibility and inventory levels and space requirements. They confirm that generic guidelines for how in-plant materials supply systems should be designed should still be the focus of further research.

Limère et al. (2012) developed a mathematical optimization model for the assignment of each individual part to kitting or bulk feeding. The mixed integer linear programming model minimizes the overall in-plant logistics costs and finds an optimal assignment. Limère (2011) describes an extension of the model.

MATHEMATICAL MODEL

The simulation model will be used to validate the results of the mathematical cost model of Limère (2011). To understand this comparison we will briefly describe the mathematical model without representing the details of the many parameters involved. For further information we refer to the original paper.

The model is a linear mixed integer programming model and assigns for every part the value of a binary variable to zero if the part should be kitted in an optimal situation and to one if the part should be supplied in bulk to the line. The model has the following objective and constraints:

$$\text{Minimize total in-plant logistics cost} \quad (1)$$

Subject to,

Weight constraint of kit container	(2)
Volume constraint of kit container	(3)
Space constraint at the border of line	(4)

The total in-plant logistics cost (1) consists of four sub-costs:

a) The operator at the line needs to pick the parts for assembly from the border of line (i.e. material façade next to the line). This can be picking from bulk containers or from kits. For bulk containers we assume two different kinds of containers, namely boxes and pallets.

b) Parts need to be supplied from the warehouse or the supermarket to the border of line. Pallets are supplied by forklifts and boxes and kits by tugger trains doing a milk run tour at constant time intervals.

c) Kits need to be prepared. The kit assembly takes place in a supermarket area.

d) The supermarket needs to be replenished from the warehouse.

Constraint (2) and (3) make sure that the optimal assignment of binary variables takes into account that the kit container can only carry a certain maximum weight and fit a certain maximum volume of parts. If more parts are assigned to kitting that can fit into one kit container, the model will automatically create two kits at that work station and the additional cost of creating and transporting this second kit will also be taken into account.

Constraint (4) imposes that all stock at the line (boxes, pallets and kits) needs to be stored parallel to the line and the space along the line is limited to the width of the work station. As such, if there is not enough space to store all items in bulk at a work station, kitting will be imposed.

SIMULATION MODEL

The model described in the previous section (similar to all other existing models described in the literature review) is based on average performances. None of the models take into account stochastic effects. This is therefore the subject of this paper. The research objective is to build a simulation model for the optimal solution from the mathematical model introduced by Limère (2011) and compare the cost results of both models. This will give us insight in the impact of variability on the choice to kit or not to kit.

Aside from the impact of stochastic effects, the simulation model also allows us to model the flows more accurately. In the mathematical model we restrained ourselves to linear functions. Walking distances were therefore approximated by Manhattan distances although the operator would in reality always walk straight to the use-point next to the line (Euclidean distance). In the simulation the walking will be modeled more realistically.

The simulation model is created with the commercial software package FlexSim. Like other commercial discrete-event simulation software packages FlexSim supports the creation of customized simulation objects (Nordgren, 2002). For this model a 'workstation' object, a 'box' object, a 'pallet' object and a 'kit' object were developed. Based on these objects the assembly line and the supermarket, where kitting takes place, could be modeled. Tuggers and forklifts are used to model the different internal transportation flows. The objects are built with standard objects of the FlexSim library and scripting is used to get the functionality needed. The main purpose for the use of customized simulation objects was to minimize the usage of computer resources and maximize efficiency of the model.

Furthermore, the model itself is generated by scripts developed in flexscript (Nordgren, 2002). This is needed to limit development time; it allows generating new models in a flexible and cost-effective way (Govaert et al., 2009). The model holds more than a thousand interconnected objects. Doing this manually would take a few days and every important structural change would take another few days, while right now it takes only a few seconds to generate the model. If a change is needed, only the custom objects need to be changed and then regenerating the model takes again only a few seconds. Aside from the time gain, even more importantly, automatic model generation avoids human errors.

A print screen of the simulation model is shown in Figure 1. The central representation (within the frame) shows the complete model with in the lower part the assembly line, in the left upper corner the supermarket for kitting, and in-between the flow paths for the tuggers and the forklifts. Above the frame a part of the kitting supermarket is shown zoomed in. You can see how this is organized in parallel aisles for all the kits. Below the frame, part of the assembly line is represented. The work stations are located at both sides of the line and every workstation has a border of line organized with pallets, boxes and kits.

PRELIMINARY RESULTS

A preliminary study was done to compare the results of the mathematical model and the simulation model. A first important observation was a difference in the results because of optional parts. To explain this, we will first define what variant parts are, and how optional parts are a special type of variant parts. Because of the variation in end products on a mixed-model assembly line, different parts need to be assembled in different end products. When a choice can be
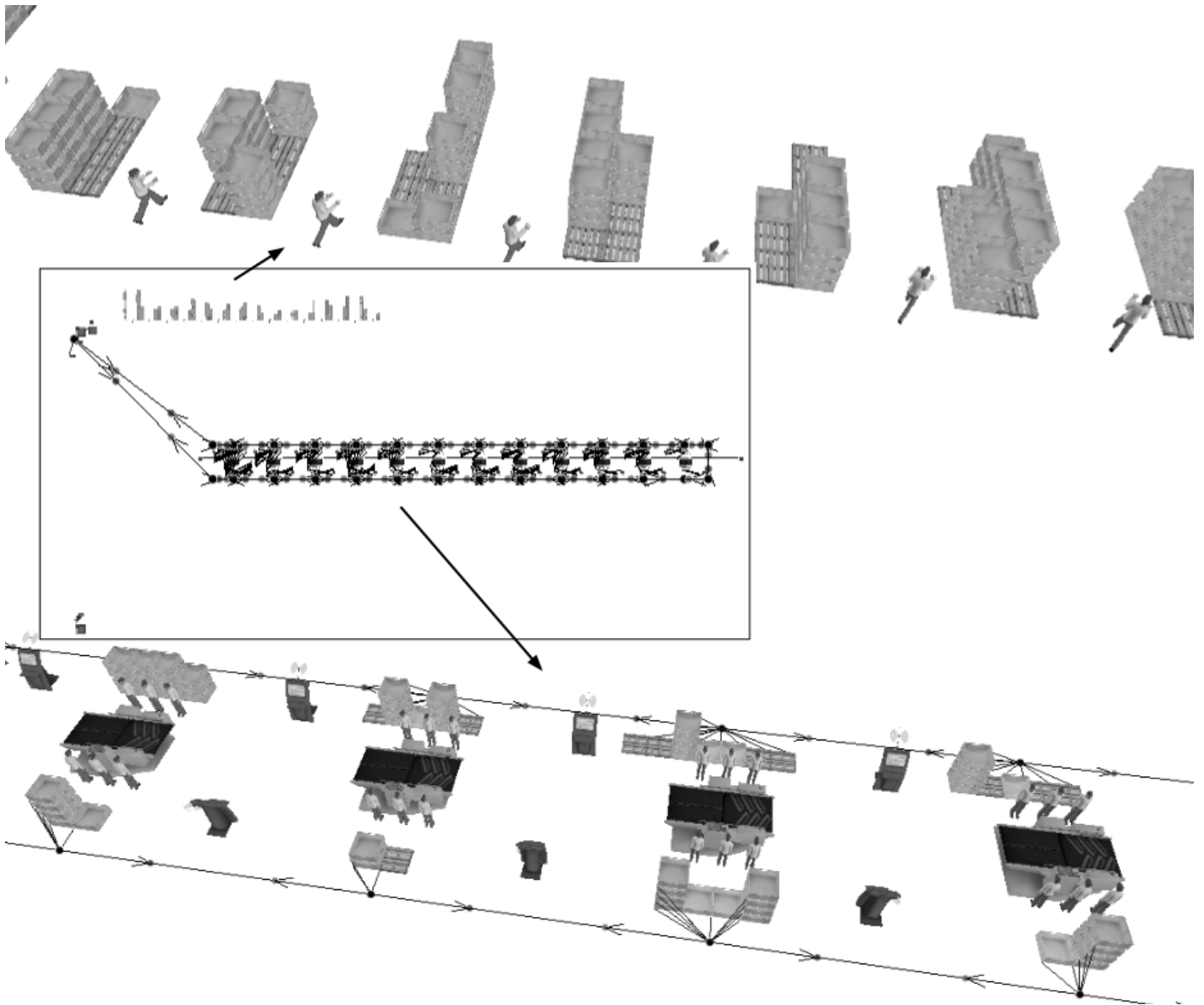
Fig. 1: Simulation model

made between a number of parts, e.g. different types of car radios, these parts are called *variant parts* of a part family. It is sure that you will never assemble two different parts of a part family, but you will make a choice. Usually, you would expect the frequency of occurrence of all variant parts of one part family to some up to 100%, e.g. either you choose radio 1, 2 , …, *n*. Nevertheless, this is not true for *optional parts*. In the case of *optional parts* it is possible that there are end products without that specific component, e.g. 5% of the cars do not have a radio installed.

To understand how the existence of optional parts leads to a difference in costs between the mathematical model and the simulation model, we need to understand how the kit preparation cost is calculated. The kit preparation cost consists of a fixed cost per kit and a variable cost depending on the parts in a kit. In the mathematical model the number of kits is calculated based on constraint (2) and (3). This means that for every part in the kit, a place is reserved with a specific volume and weight. If a part has multiple variants, only one place has to be reserved because every end product will only choose one variant of each part. In the case of optional parts a place is thus also reserved, even if that part is not needed in the specific end product in line. In the special case where only a few optional parts are consolidated in a kit, and all these parts are not required for the next end product in sequence, the mathematical cost model will incorrectly count the fixed cost for making this kit, although in reality no kit will be made.

Although this is an extraordinary case, we decided to further test the model without the inclusion of optional parts to avoid distorted results.

CASE STUDY

In the case study modeled, 438 parts need to be supplied to an assembly line of 23 work stations. A hybrid solution is found as the optimum from the mathematical model. 146 parts are supplied in bulk and the remaining 292 parts are grouped into kits. Table 1 gives an overview of the part dataset and the line feeding policies assigned.

Table 1: Case study – part data set

| | Number of parts | | | | |
| | Originally packaged in box | | Originally packaged in pallet | | |
	Kit	Bulk	Kit	Bulk	Number of kits
Station 1	23	4	10	6	1
Station 2	0	15	0	0	0
Station 3	27	8	0	2	1
Station 4	17	4	8	4	2
Station 5	30	4	3	3	1
Station 6	0	2	0	0	0
Station 7	0	4	0	0	0
Station 8	0	7	0	0	0
Station 9	28	8	7	1	2
Station 10	27	7	2	2	1
Station 11	13	4	0	2	1
Station 12	0	2	0	0	0
Station 13	0	3	0	0	0
Station 14	0		0	1	0
Station 15	7	4	4	0	1
Station 16	0	3	0	4	0
Station 17	13	3	1	2	1
Station 18	10	7	9	0	1
Station 19	23	4	1	0	1
Station 20	14	8	15	0	2
Station 21	0	2	0	1	0
Station 22	0	5	0	0	0
Station 23	0	10	0	0	0

The frequencies of usage of the parts vary between occurrence in 5% of the end products till 100%. The histogram represented in Figure 2 shows the distribution of the frequencies over all parts. In the simulation model, the final assembly sequence is obtained by random sampling part usage information from Bernoulli distributions with the respective frequencies.
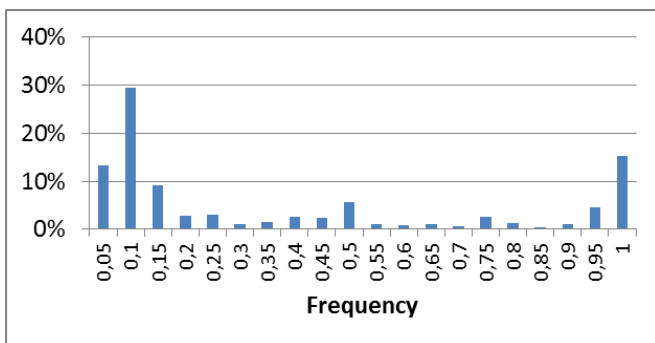

Fig. 2: Part frequencies

RESULTS

Picking at the line
To model the walking distances at the line the mathematical cost model uses a linear approximation of the real walking distances. The reason for this is keeping the CPU time for solving the problem acceptable. In Figure 3, the bold dotted lines represent the real walking paths towards the border of line. This is also how the walking paths are modeled in the simulation model. In the mathematical model, however, the distance is modeled as if the operator is first walking straight to the border of line (1.5m) and only then will walk along the border line to the required part container. This will give an over-estimation of the walking distances. To avoid this, the 1.5m to walk towards the border of line is set to 1m in the calculation.
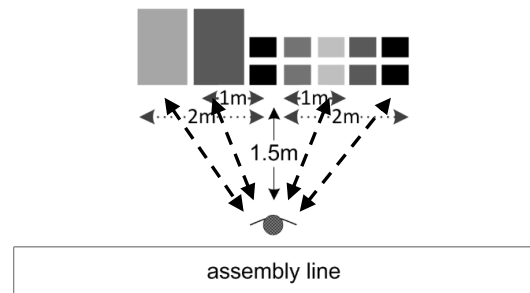

Fig. 3: Real and approximated walking path

Nevertheless, the approximation in the mathematical model will result into inaccurate walking distances. Figure 4 shows, for the case study, the walking distances towards all parts in bulk for the two models. The simulation model seems to have longer distances than the mathematical model. Another reason for this is that the simulation takes into account that when there are kits, which are always positioned closest to the operator, they take up the best places at the border of line and the other part containers will be positioned further away. However, when we calculate the average difference in walking distances, we notice it is limited to 1.66%. Moreover, if we check the total cost for picking at the line, both from kits and from bulk, we notice that the costs differ by only 0.2%.
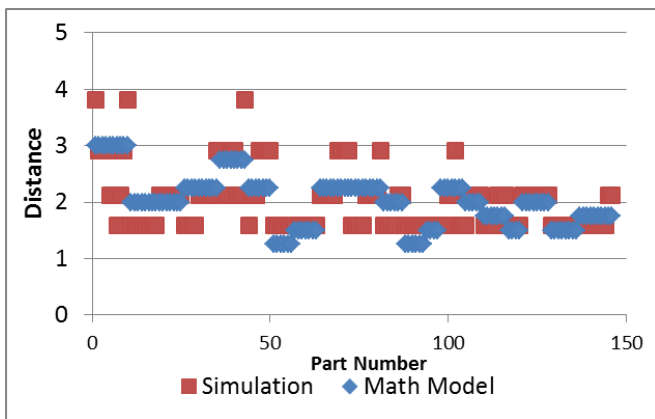
Fig. 4: Distribution of the walking distances

Yet, even though the average walking distances do not vary, the different distributions might have an impact on the choice for a particular line feeding method. It is therefore important to also consider the more accurate walking distances in the simulation. If we want to find an optimal line feeding solution in the future, which takes into account these accurate distances, a simulation-based optimization approach might be considered.

Internal transport

An important part of the model where the stochastic character of the part usage has an effect, is the internal tugger transport. We already mentioned that the tuggers drive a milk run tour at constant time intervals and a tugger has a capacity for pulling a certain amount of boxes or kits at once. Because of the variability of demand, it will not be possible to fully utilize the capacity of the tuggers.

For the kitting tugger there is no variability in demand since kits usage is perfectly predictable, it evolves synchronized with the takt time of the line. The predictability of demand is one of the major advantages of kitting. This is true especially since we are not considering optional parts. The kit tugger can drive at intervals for which the total capacity of the tugger is utilized.

However, for the tugger that transports the boxes to the line, there is a considerable variability in demand. Because of this reason, some tugger runs will be almost empty, while for peak loads the capacity of the tugger might be tight. To take this into account in the mathematical cost model, we used a parameter ρ representing the average utilization of the box tugger. This parameter needed to be estimated beforehand. Thanks to the simulation model we can now do some testing, with changing time intervals for the tugger, to find a valid capacity utilization. The mathematical model can be run again iteratively with the capacity utilization found until the optimal solution from the mathematical model does not change anymore. For the case study, the utilization for a tugger train, driving a milk run tour every 40 minutes, is found to be 56.6%.

Kitting cost

The kitting cost could be modeled accurately. Because of the use of Bernoulli distributions for the generation of an assembly sequence, kits can be prepared at almost constant

efficiency. In future research, we would also like to test how different assembly sequencing, with some kind of leveling or batching of demand, could influence the efficiency of kit preparation when kits are assembled in batches.

CONCLUSION

We created a simulation model in FlexSim and an automatic model generator for the analysis of in-plant logistics systems. With the help of the automatic model generator different case studies can be modeled without a lot of additional effort or costs.

A case study is studied to compare the results of the stochastic simulation model with a deterministic mixed integer linear programming model from previous research. Results are reported. This study is still in a preliminary phase. Further investigations will be done to examine the impact of specific production variations, and different case studies. Furthermore, we want to check the impact of consolidating the replenishment of kits and boxes in one milk run tour that runs at smaller time intervals.

Finally, since both models, mathematical and simulation, have advantages, in the future we will also aim for an integration of both in a simulation-based optimization approach.

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