



Samsung Electro-Mechanics

Introduction

The Samsung Electro-Mechanics (SEM) Co. is one of the largest manufacturing companies in Korea. The company has 13 operation divisions in Korea and 15 overseas. They produce high-tech integrated components and mechanical devices for cell phones, computers, etc. For SEM, we analyzed manufacturing processes from one of the divisions in Korea. These processes consist of several manufacturing steps such as drilling, drying, packaging, etc.



Fig. 1 SEM factory in Suwon

Goal of the Analysis

In SEM, a MES (Manufacturing Execution System) has been developed to support manufacturing managers to execute manufacturing processes and make better decisions by providing useful information on the processes. In the MES, analyzing the manufacturing process is one of the important functions.

To analyze the data from the MES, the Equipment Optimization Technology (EOT) department in SEM has used several data analysis techniques, such as statistics, data mining, etc. However, while the techniques work well to analyze data for a specific manufacturing task, they have difficulties to provide overall

process level analysis results, such as overall performance, manufacturing patterns, etc. Thus in this research, we applied process mining techniques to analyzed manufacturing processes in SEM.

Event Log

For the case study, we used the event logs from the MES in SEM. A basic unit in manufacturing is a lot, and we used a lot number as a case ID, which is an identification number assigned to a particular quantity or lot of material. The obtained event log contained all the tasks and the machines used for the lots manufactured from May 2012 to October 2012.

- 11,226 cases (lots that were manufactured)
- 900,542 events (activities performed for these lots)
- 361 different tasks (e.g. *CNC drilling, marking, drying, packaging*)
- 1,217 different machines

Process Mining Results

The purpose of the analysis is to show the applicability of process mining techniques in manufacturing process analysis. After the in-depth discussions with the EOT department, the following questions were posed:

- What is an actual process flow in SEM?
- Are there any abnormal traces of a lot?
- Are there any bottleneck points in the process?
- How are the machines utilized?

For these questions the following results were obtained:

Discovering Process model

For the case study, we derived the process model by applying Heuristic mining. Figure 2 shows a screenshot of the derived process model for one of the SEM products. It starts with the *Input* task and finishes with the *Packaging*. The model is useful to understand the manufacturing process flows. It consists of three phases: preprocessing, main manufacturing, and inspection. It also shows the number of lots moving between activities.

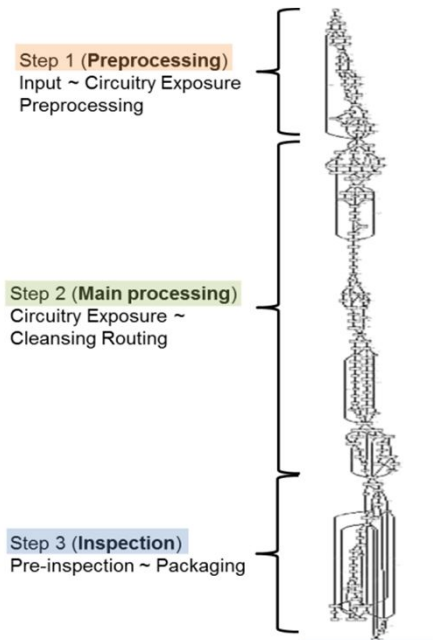


Fig. 2 Derived process model

Conformance Checking

Conformance checking provides a fitness value of the derived process model. Figure 3 shows a fragment of the conformance checking results. The fitness value of the overall process is 0.9962. It indicates that almost all of the traces fit with the derived model. For the missing and remaining tokens, we performed further analysis with the LTL checker and found some abnormal flows. For example, one of the major abnormal flows is the flow from the *Delivery Inspection* task to *Final Test* task. It means that some unexpected issues occurred in the inspection for delivery and a lot moved to the final test task to find the problems. However, since very few traces had those abnormal flows, we can say that the manufacturing process in SEM is well managed.

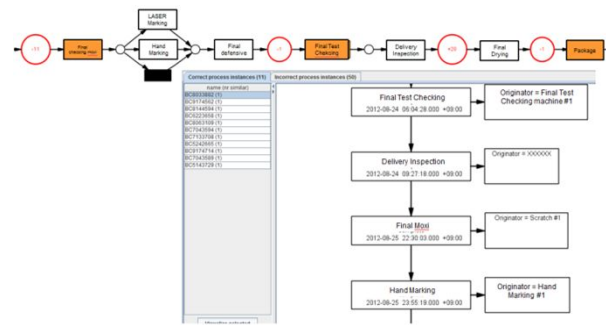


Fig. 3 Conformance and LTL checking result

Machine performance analysis

Since manufacturing equipment is a crucial resource in the factory, we had performed performance analysis in the perspective of resources. In the analysis we were able to see an unbalanced usage of machines. For example, Table 1 shows the usage frequencies of the seven machines for the *packaging* task. Machine N28027 was used 5,612 times, while machine N14074 was used 2 times.

Machine	Package
N28026	5,612
N28027	2,965
N20031	2,143
N20030	500
N14074	2
N28025	2
N28146	2

Table. 1 Resource by task matrix for the *packaging* task

In addition, we calculated the average working time for the machines. Figure 4 shows the performance values of the seven machines. The bars represent frequencies. The red line and the green line show average and median working times for each machine respectively. The dashed line indicates the average working time for the *packaging* task. In the figure, we found that machine N20031 has the longest working time.

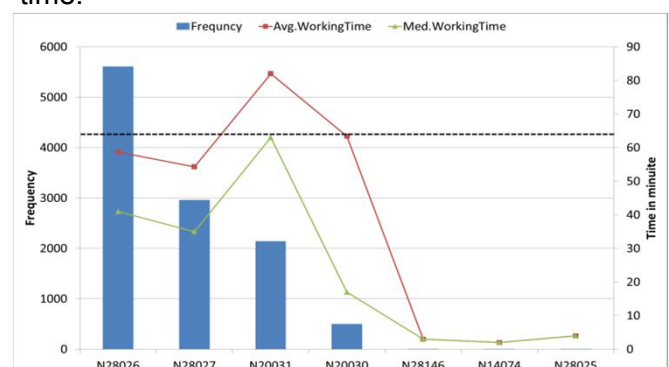


Fig. 4 Performance of the seven machines for *packaging* task

To investigate the event-level information for machine N20031, we performed the dotted chart analysis in Figure 5. The chart shows that about 90% of cases finished within 5 hours. However, there are a few cases which took more than 1 day increasing the average working time. This shows that some extreme cases result in the overall performance poor.

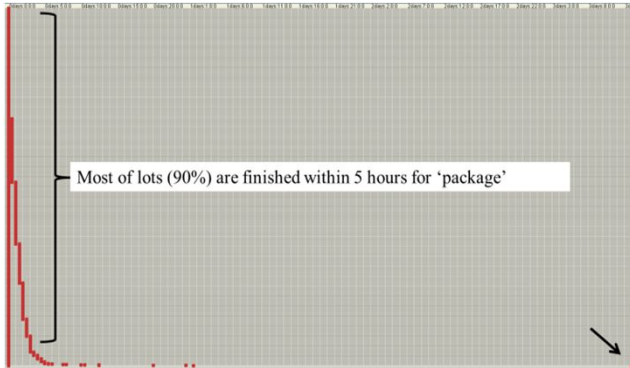


Fig. 5 Dotted chart for the machine N20031

Conclusion

Based on the manufacturing event logs in SEM, we derived the process model and performed the conformance analysis and the machine performance analysis. The derived process model shows actual process flows in the factory and is used to understand the manufacturing process. The conformance checking shows how traces fit with the derived model. The machine performance analysis shows the utilization of their resources. The analysis results were presented to the managers of SEM, who were impressed by the obtained results. The results will be used to improve their processes. In particular, the performance parameters will be used for a factory simulation in the e-FEED system that is the integrated design and analysis system for optimized manufacturing line development. For the next step, we will implement a process mining software and use it as a process monitoring and analysis tool in SEM.