

Optimizing Assembly Line Efficiency Using Discrete-Event Simulation

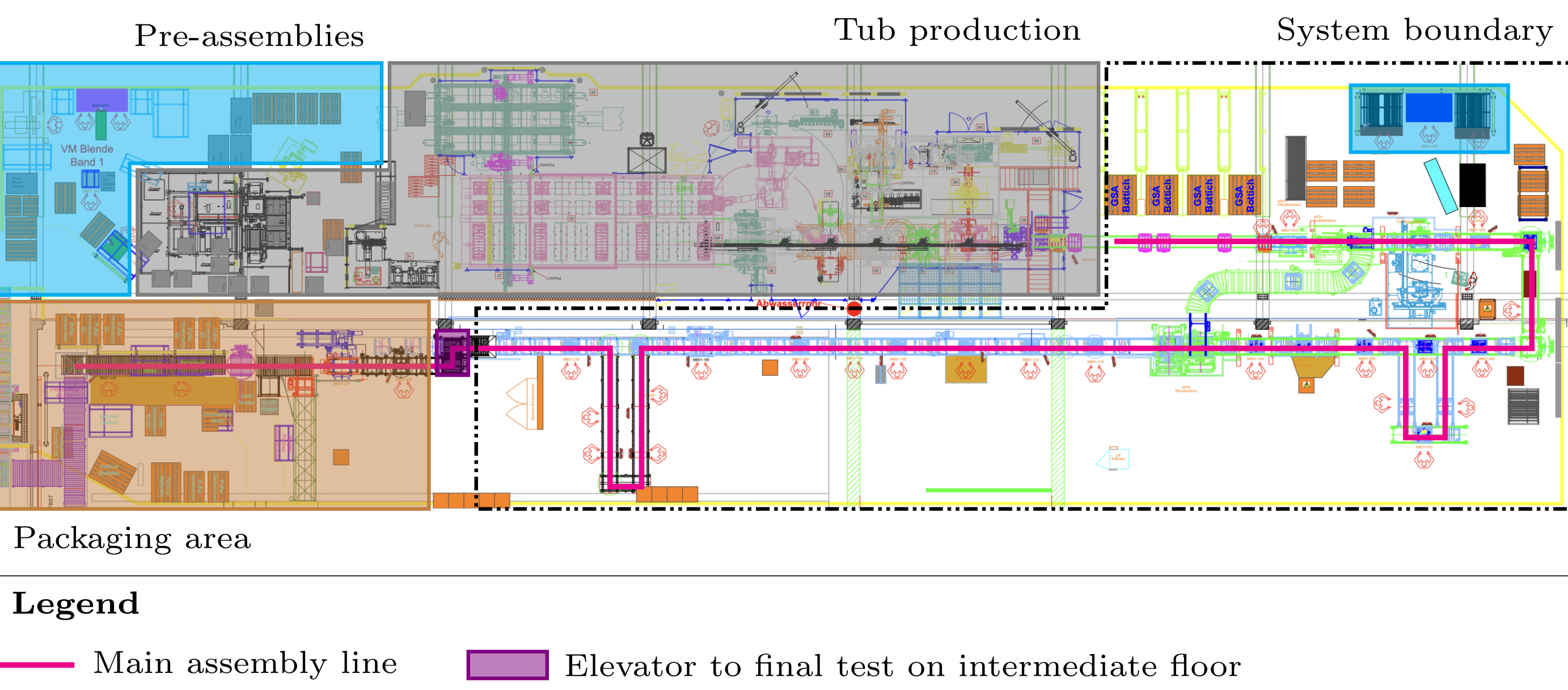


Fig. 1: Assembly line layout

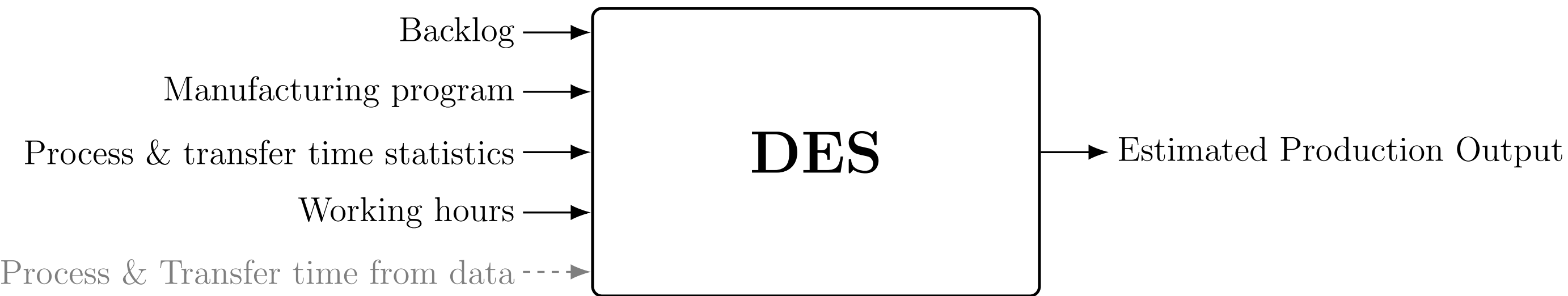


Fig. 2: Input / Output diagram of discrete-event simulation model

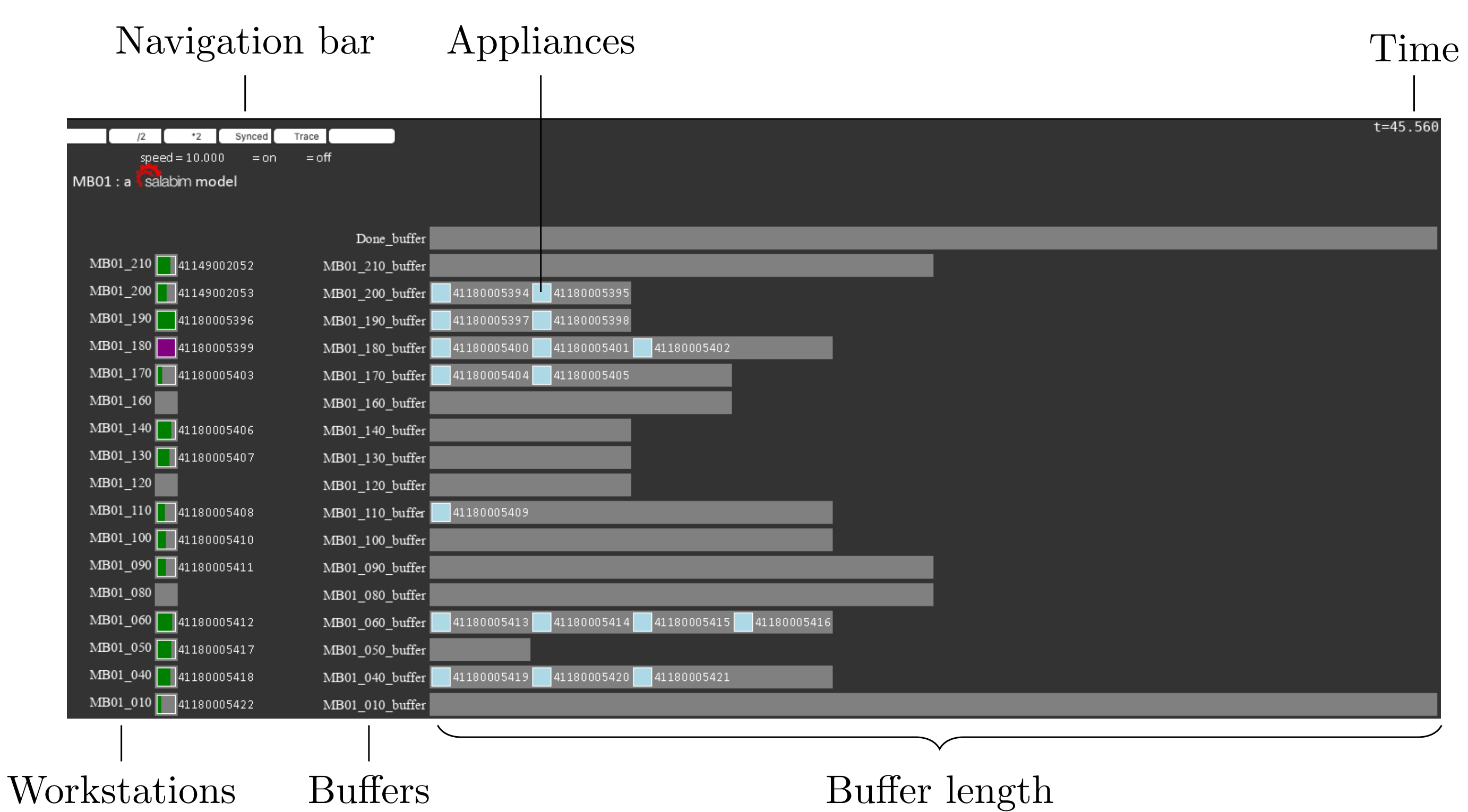


Fig. 3: Animated discrete-event simulation model

Background and Motivation

V-ZUG AG is a leading supplier of household appliances in Switzerland. Due to the expensive production site in Zug, V-ZUG AG has put a lot of effort into transforming towards a vertical factory over the past few years. The goal is to maximize efficiency while minimizing the required footprint. Therefore, smart manufacturing systems are required.

The challenge for modern manufacturing companies is to analyse and make use of all the information provided. Especially complex systems, such as an assembly line, generate a lot of data which is often not used. However, this data can often be very useful not only to get a better understanding of the process itself, but also to make data-based decisions and optimize the process. In the context of an assembly line, efficiency is highly dependent on the order in which the different types of appliances are produced. This thesis focuses on the assembly line for dishwashers (cf. Fig. 1).

Approach

In order to create a digital representation of the real-world assembly process, a discrete-event simulation model was built using the Python library Salabim (cf. Fig. 2 & 3). Based on real data gathered from the process, statistical models for the processing time on the workstations and the transfer time between them are derived. At the end, the assembly order is optimized with a genetic algorithm.

Results

The simulation model is found to make a good approximation of the actual assembly line output which often lies within the $\pm 5\%$ - tolerance. However, sometimes, the model's approximation is much higher than the actual output achieved. By successively integrating the real data, this mismatch can be illustrated (cf. Fig. 4). Although the model contains a lot of uncertainty, this can also be a sign for an unforeseen event that happened during that day (e.g. machine downtime, etc.). The genetic algorithm uses this model to optimize the assembly order with regards

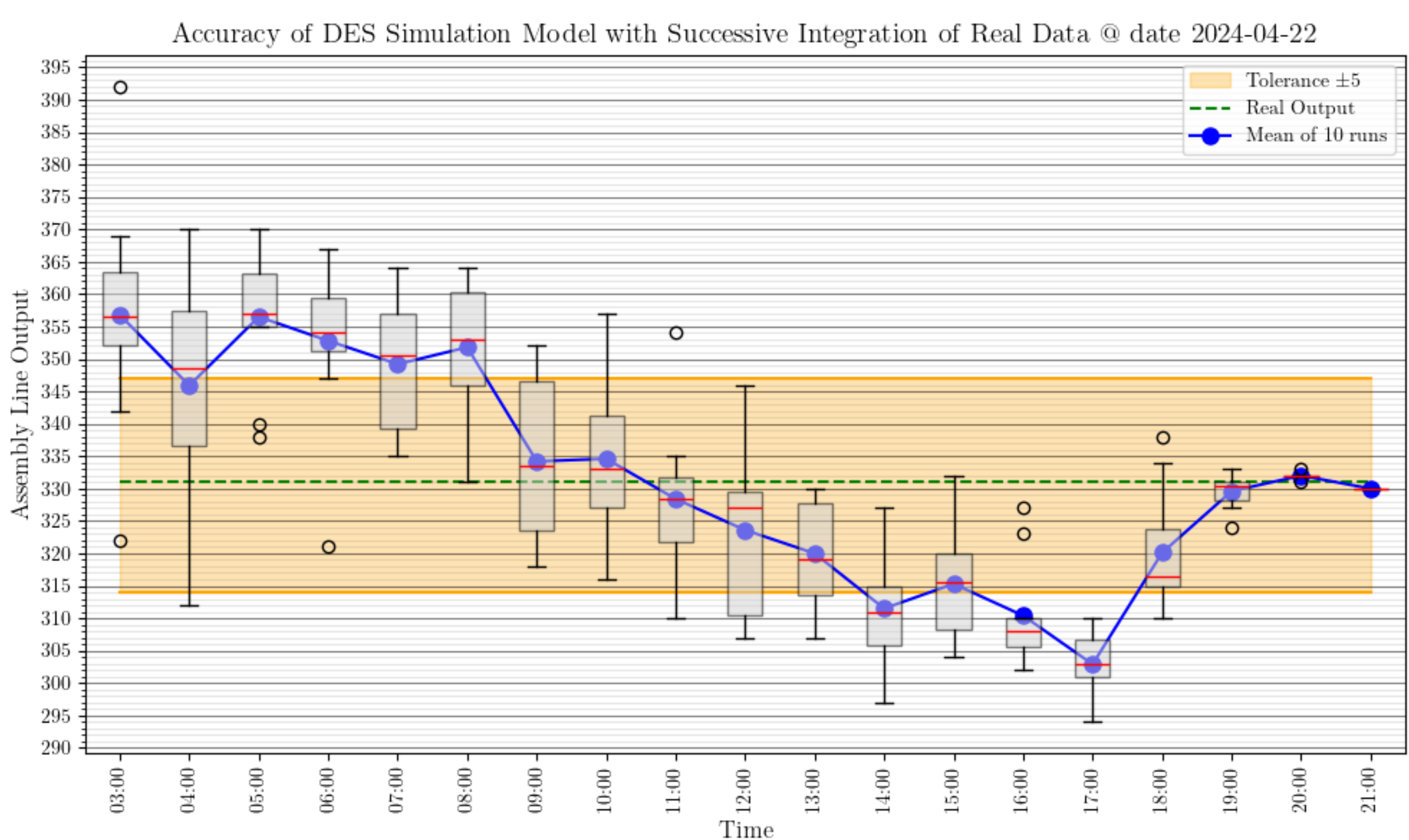


Fig. 4: Estimated assembly line output according to simulation with successive integration of real data

Property	Order																								Scores
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
Comfort Level		2T		4T		6T				4T											2T				$c_1 = 1$ $c_2 = 0$ $c_4 = 1$ $c_5 = 1$
Width			55												60										$c_3 = 1$
Capacity				NR						GR							NR					GR			$c_6 = 0.83$
Drawer				No					Yes								No								$c_7 = 0.86$
Colour		C	W	I	N	C				I						W	C	N	C	W	I				$c_8 = 0.52$
Total Score																									6.21

Fig. 5: Order of constraint-relevant properties of the real assembly plan

Constraint	Order																								Score
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	
Comfort Level		2T		4T		6T		4T	6T			4T				2T	4T				2T				$c_1 = 0.79$ $c_2 = 0$ $c_4 = 1$ $c_5 = 0.67$
Width			55		60	55				60						55					60				$c_3 = 0.81$
Capacity				NR		GR				NR			GR				NR					GR			$c_6 = 0.75$
Drawer				No					Yes								No								$c_7 = 0.86$
Colour		C	W	I	N	C				I						W	C	N	C	W	I				$c_8 = 0.52$
Total Score																									5.4

Fig. 6: Order of constraint-relevant properties of the optimized assembly plan

to certain soft-constraints as well as the required assembly time according to the simulation. The optimization of an example assembly program led to an estimated time reduction of 30 minutes (cf. Fig. 5 & 6). With a theoretical cycle time of 85 seconds, this would correspond to 20 appliances which could potentially be produced more that day.

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