to evaluate the respective influence. To test overbooking, β = {-0.01, -0.02, …, -0.05} for α = {0.05, 0.1}, and to test underbooking, β = {0.01, 0.02, …, 0.05} for α = {0.05, 0.1}, are simulated in the numerical study. For the evaluated planning systems, their planning parameters are varied to perform a fair performance comparison. The respective parameter ranges have been identified in preliminary simulation runs. For RPS, the planning parameters varied are lot size *LS* and reorder point *RP*. For MRP, these are safety stock *SS*, lot sizing policy (with the respective parameter) and planned lead time *PLT*. For MRP the lot size policies of fixed order quantity (FOQ) with *LS* (lot size) as parameter and fixed order Period (FOP) with *NP* (number of periods) as parameter are evaluated. For both, MRP and RPS, the same planning parameters are applied for item 10 and 20. In detail, the MRP parameters have the following ranges: *SS*={0, 200, 400, 600, 800, 1200, 1600}, for FOQ *LS*={200, 400, 600, 800, 1200, 1600, 2400, 3200}, for FOP *NP*={1, 2, 3, 4, 5}, and *LT*={2, 4, 6, 8}. For RPS, the same lot sizes LS as for FOQ in MRP are used and *RP*={2000, 2400, …, 4800} are applied. For MRP planning, the used safety stock parameter *SS* also corresponds to the initial stocking quantity, and for the RPS the *RP* parameter value is the initial stocking quantity. In total 36,192 (22,272 FOQ, 13,920 FOQ) different iterations for MRP and 5,568 for RPS are evaluated with the simulation model. Each one is replicated 10 times per iteration, to account for the stochastic influence during simulation, resulting in 417,600 individual replications. The representation of confidence intervals has been omitted, however, all mayor difference in costs are signification with confidence level of lower than 0.05. Confidence levels of representation are not included for clarity purposes.

4 NUMERICAL RESULTS

In this section, the stated research questions are answered using the results of the conducted simulation study. As stated in the introduction, we investigate in which situations standard MRP with its rolling horizon planning capability benefits from uncertain demand forecasts and what conditions lead to a better performance of RPS. The discussed cost results represent the overall costs per period computed by the sum of finished goods inventory (FGI), Work in Progress (WIP) and tardiness per unit. For FGI a costing factor of 1 is applied, for WIP 0.5 and for tardiness of 19. The relation of WIP and tardiness costs represents a target service level of 95 %. Inventory costs are twice of WIP as it is more costly to store end items.

4.1 Effects of Unsystematic Forecast Uncertainty

To answer RQ1 and discuss the effect of forecast uncertainty on MRP and RPS, Figure 2a shows the minimum costs with respect to α which are reached for MRP with *FOQ*, MRP with *FOP*, and *RPS* when the planning parameters are optimized for the medium shop load scenario.

In general, Figure 2a shows that a higher forecast uncertainty, which also implies higher final order amount uncertainty, leads to high costs for both methods MRP and RPS. Further, the results show that both lot sizing policies, i.e., FOP and FOQ perform very similar in situations without forecast bias. For very low α values, which imply a very low uncertainty for the final order amount, the application of demand forecast in MRP leads to higher costs. The reason is that applying forecast updates in MRP leads in some situations to additional orders, however, the number of updates implies only low final order amount disturbances and can better be handled with RPS. The detailed analysis of safety stock *SS* for MRP shows that both FOP and FOQ react with a higher safety stock on a higher forecast uncertainty (see Figure 2b). Note that for all uncertainty settings the *PLT*=2 was optimal in MRP. Related to RPS, higher α values, which lead to higher fluctuations in final order amounts, imply higher optimal *RP* values (see Figure 2b), which is in line with inventory control literature where the optimal reorder point should be the maximum of demand during the replenishment time. An interesting finding is, that higher forecast uncertainty (and final order amount fluctuations) lead for MRP and RPS to higher production lot sizes. Specifically, the finding that FOQ and RPS have the same optimal lot size for an unbiased forecast value between 0.025 and 0.175 is interesting (see Figure 2c). In general, a higher lot size, leads to an overall higher inventory level and to a lower utilization. The higher inventory level helps to avoid a stock out situation and the lower utilization enables shorter lead times and a more flexible production process. Additionally, the finding confirms the intuitive expectation, that the MRP FOQ lot size and the reorder point lot size are very similar.

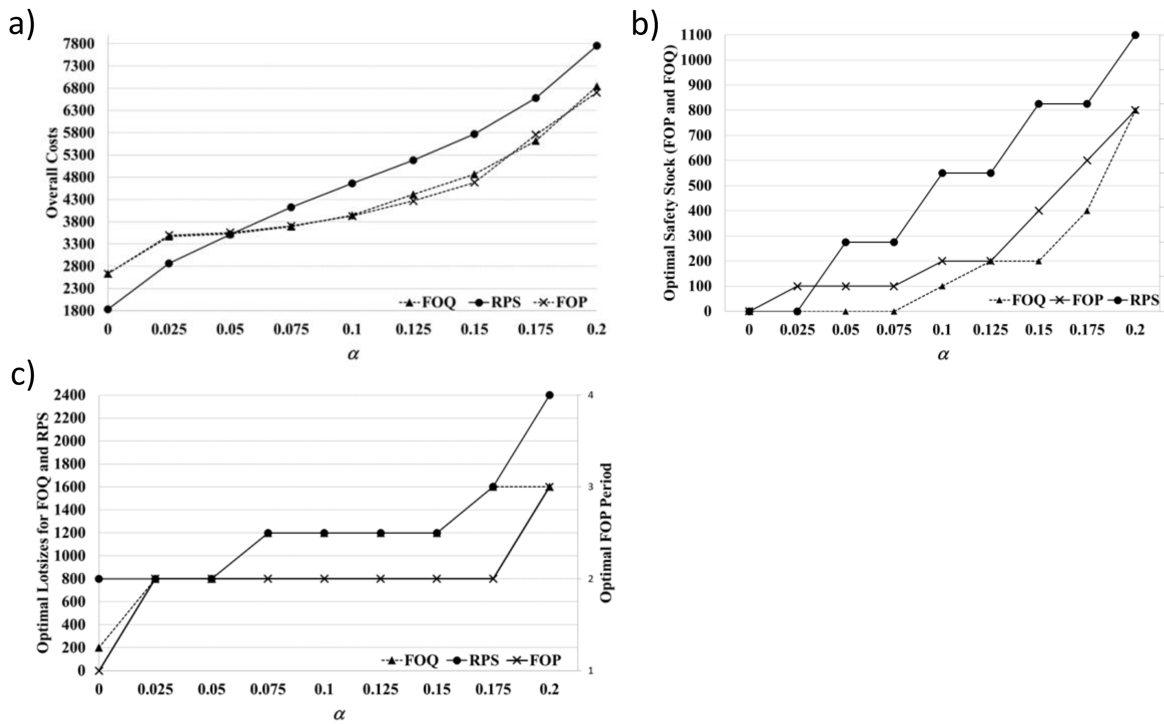

Figure 2: Results unbiased forecast error: comparison a) cost, b) safety stock vs. reorder point, c) lot size.

4.2 Overbooking and Underbooking Comparison

To answer RQ2 and RQ3 and evaluate the effect of overbooking and underbooking on the optimal planning method, Figure 3 shows the minimum costs for MRP (with FOP and FOQ) and RPS for medium shop load and α=0.05 as well as α=0.1 with respect to the tested systematic forecast bias value β.

Since the modeling assumptions concerning forecast bias lead to higher long-term forecasts for overbooking and lower long-term forecast for underbooking, the demand forecast update uncertainty σ_ε is influenced accordingly, i.e., higher β implies higher uncertainty for overbooking and lower uncertainty for underbooking, compare to Equation (3). Related to RQ2, the results show that overbooking with high forecast uncertainty and forecast bias leads to the highest cost. For underbooking, i.e., the forecasts are too low, RPS works better when forecast uncertainty α is low (see Figure 3a) but RPS performs worse in all other situations (see Figure 3b–d). In the situation underbooking and low α (see Figure 3a) FOQ works better than FOP for moderate to high systematic forecast bias. In all scenarios with high α, MRP-FOP and MRP-FOQ perform very similar. In the underbooking situation for low α and high forecast bias, we see that MRP-FOQ performance is superior to MRP-FOP performance. The study shows for scenarios with overbooking, always MRP outperforms RPS. Contrary to MRP, RPS ignores the forecast information, but its performance is strongly dependent on the demand uncertainty. This implies in the underbooking case for higher β values (these lead to lower long term forecasts) the final order amount fluctuation is lower. Therefore, RPS leads to lower costs for higher β values and the opposite holds for overbooking.

4.3 Detailed Analysis of Underbooking Behavior with Low Forecast Uncertainty

Table 2 shows the overall costs and the optimal planning parameters for MRP and RPS method for α=0.05 for three different utilization values (i.e., low, medium, and high). The Δ sign indicates the delta of costs in percentage calculating $\Delta = 100 * (cost_{RPS} - cost_{MRP})/cost_{MRP}$. The study shows that for low forecast uncertainty and a low utilization level, RPS performs better than the MRP method. In most other scenarios MRP outperforms RPS (see Table 3 in Section 4.4). The summarizing Table 2 shows that in situations with high-capacity buffer (i.e., low utilization level) and low demand variations, RPS is more efficient than MRP. In this situation MRP cannot benefit from using the demand forecast information, especially as it is biased and too low values are forecasted, i.e., a higher backorder risk occurs.

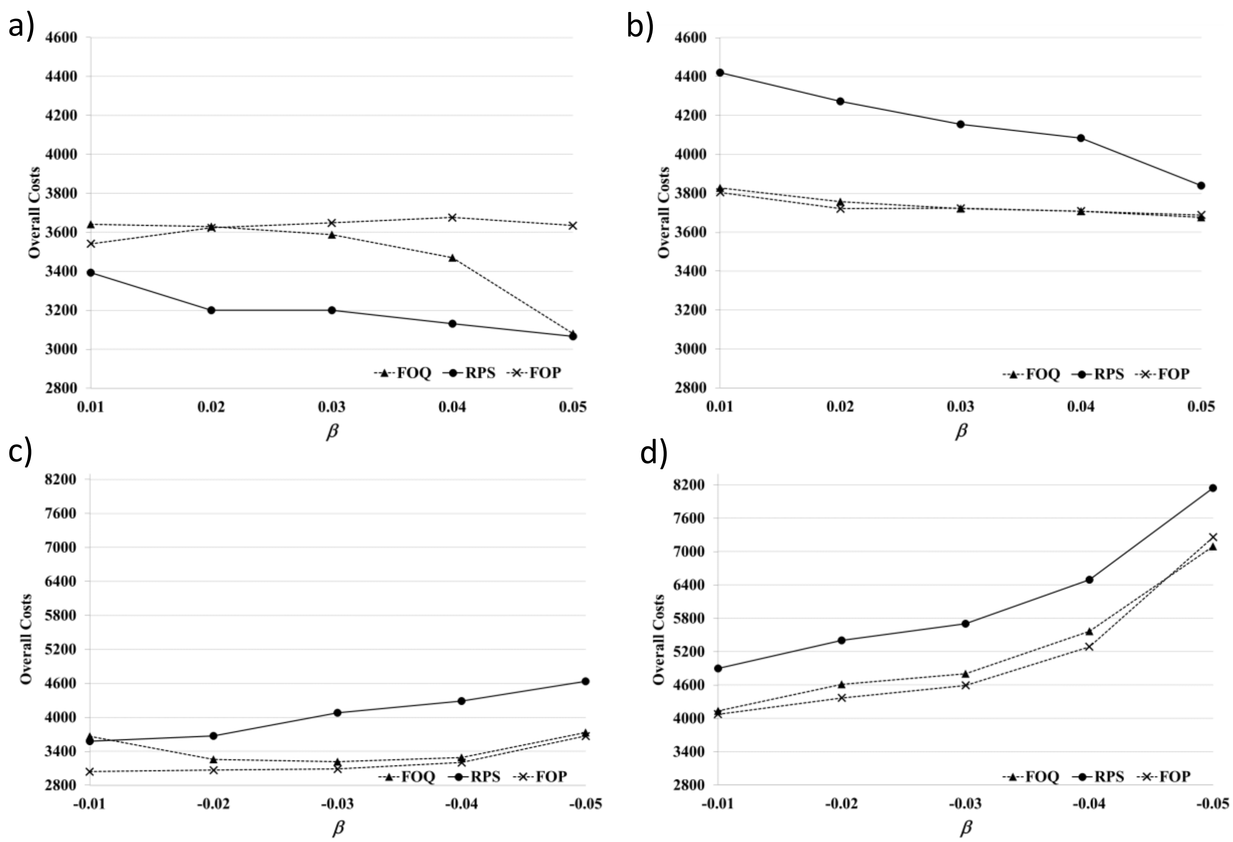

Figure 3: Overall costs for: underbooking a) α=0.05, b) α=0.1, and overbooking c) α=0.05, d) α=0.1.

The lot size for RPS is quite stable for the RPS system whereas the reorder point increases with respect to the planned utilization level. Analyzing the parameter optimization results, we see that the optimal lead time for MRP is almost constant for all scenarios. Note that this finding is limited by the very streamlined production system with one BOM-level. For MRP the results show that in 11 out of 18 scenarios FOP is superior to FOQ. In general, the investigation shows that for low and medium utilization levels in the underbooking scenario with low forecast uncertainty RPS is superior compared to MRP. For high utilization values results do not confirm this finding.

4.4 Overall Cost Comparison

To discuss the sensitivity of the results, Table 3 presents the overall costs of MRP and RPS with respect to different levels of the forecast uncertainty α, different levels of forecast bias β, and three different utilization levels. The Δ sign represents as defined in Section 4.3 the cost delta in % comparing MRP and RPS costs. The first two columns (MRP/RPS/Δ) stand for the underbooking scenario ($\beta > 0$) whereas the third and fourth column show the results of the overbooking ($\beta < 0$) scenario.

The results show that for most investigated scenarios RPS is only superior in the underbooking scenarios ($\beta > 0$), when forecast uncertainty α is low and utilization levels are low or moderate. This is also in line with the findings discussed in Section 4.3. In all other situations, MRP and the use of forecast information leads to better overall costs than using RPS as planning method. For these scenarios, the integration of forecast information leads to a superior setting compared to the RPS system where production orders are issued based on the historical order amounts and the predefined static reorder point. When comparing the results of column one and three (low α) with column two and four (high α), results show that higher forecast uncertainty leads to higher costs and, specifically for low and medium utilization, to a higher cost reduction potential when MRP is applied. A managerial insight is that even uncertain and biased forecasts can often to be exploited by MRP, specifically on high uncertainty of final order amounts.

Table 2: Optimal costs and optimal planning parameters for underbooking and α=0.05

		RPS			MRP					Cost Δ % RPS/MRP
	low util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3034	2000	800	3451	FOQ	800	2	0	-12.1
	0.01	2953	2000	800	3575	FOQ	800	2	0	-17.4
	0.02	2878	2000	800	3664	FOP	2	2	100	-21.5
	0.03	2887	2000	800	3463	FOQ	800	2	0	-16.6
	0.04	2863	2000	800	3402	FOQ	800	2	100	-15.8
	0.05	2842	2000	800	3059	FOQ	800	2	0	-7.1
		RPS			MRP					Cost Δ % RPS/MRP
	med util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3512	2400	800	3526	FOQ	800	2	0	-0.4
	0.01	3393	2000	800	3541	FOP	2	2	100	-4.2
	0.02	3201	2000	800	3623	FOP	2	2	100	-11.6
	0.03	3200	2000	800	3589	FOQ	800	2	100	-10.8
	0.04	3130	2000	800	3469	FOQ	800	2	200	-9.8
	0.05	3065	2000	800	3079	FOQ	800	2	100	-0.5
		RPS			MRP					Cost Δ % RPS/MRP
	high util	costs	RP	LS	costs	best method	LS/FOP	PLT	SS	
β	0	3885	2400	1200	3522	FOP	2	2	100	10.3
	0.01	3824	2400	800	3514	FOP	2	2	100	8.8
	0.02	3647	2400	800	3580	FOP	2	2	100	1.9
	0.03	3530	2400	800	3618	FOQ	1200	2	0	-2.4
	0.04	3482	2400	800	3606	FOQ	1200	2	100	-3.4
	0.05	3447	2400	800	3203	FOQ	800	2	100	7.6

5 CONCLUSION

This article describes a performance comparison of standard MRP and RPS planning methods by the means of simulation. A simulation model to study a multi-item single stage production system is developed and the differences in the performance of MRP and RPS are measured analyzing overall costs which are the sum of inventory and tardiness costs. For different levels of the forecast uncertainty, different levels of systematic forecast bias (i.e., overbooking and underbooking), and three different utilization levels, the optimal planning parameters for MRP and RPS are identified by a simulation study. A full factorial experiment design is used to find the superior planning parameter setting and discuss the optimal overall costs. The study shows that for most scenarios MRP outperforms RPS, i.e., the integration of forecast information leads to a planning advantage even if it is biased. Only in the underbooking scenarios when forecast uncertainty is low, RPS leads to better results than MRP. In these mentioned scenarios, the integration of uncertain and biased forecast information provides too less value for MRP, and the low uncertainty of final order amounts leads to advantages of the RPS method as in these situations low reorder points are sufficient. For the scenarios without forecast bias we see that the higher the forecast uncertainty, the higher are the overall costs and the higher the inventory level that is needed. For comparing overbooking and underbooking, the results confirm that in general overbooking is more beneficial for MRP and the implied higher risk of shortages in underbooking partially favors RPS. For overbooking, the cost advantages comparing MRP with RPS reach from 8 % to 30 %. For unbiased scenarios we find that RPS only performs better if the uncertainty of final order amounts is very low, in all other unbiased scenarios MRP outperforms RPS. Overall, the results show that there is no significant difference between the two tested MRP lot sizing policies FOP and FOQ for the scenarios without forecast bias. The parameter optimization results bring us to the finding that the best reorder point is always higher than the identified safety stock in MRP. Another interesting finding is that higher forecast uncertainty also leads to higher lot sizes. The higher lot sizes cause lower production system utilization and, therefore, increase flexibility for the demand uncertainty which has a positive effect on the production system performance. In further research activities, forecast evolution could be extended with shifting demand feature and for this also optimal parameter setting for MRP and RPS should be tested. The investigation of a forecast correction method in the scenario with biased forecast information and its costs performance for more complex production systems also need further investigation.

Table 3: Comprehensive overall cost comparison.

low util		α=0.05			α =0.1		
		MRP	RPS	Δ %	MRP	RPS	Δ
β	0	3451	3034	-12.1	3765	4082	8.4
	0.01	3575	2953	-17.4	3719	3785	1.8
	0.02	3664	2878	-21.5	3661	3652	-0.2
	0.03	3463	2887	-16.6	3679	3600	-2.1
	0.04	3402	2863	-15.8	3696	3532	-4.4
	0.05	3059	2842	-7.1	3675	3378	-8.1
med util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3526	3512	-0.4	3928	4665	18.8
	0.01	3541	3393	-4.2	3804	4419	16.2
	0.02	3623	3201	-11.6	3721	4273	14.8
	0.03	3589	3200	-10.8	3721	4155	11.7
	0.04	3469	3130	-9.8	3707	4084	10.2
	0.05	3079	3065	-0.5	3677	3840	4.4
high util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3522	3885	10.3	4463	5163	15.7
	0.01	3514	3824	8.8	4144	4695	13.3
	0.02	3581	3647	1.9	3937	4553	15.6
	0.03	3618	3530	-2.4	3859	4460	15.6
	0.04	3606	3482	-3.4	3744	4325	15.5
	0.05	3203	3447	7.6	3690	4189	13.5

low util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3451	3034	-12.1	3765	4082	8.4
	-0.01	2650	3100	17.0	3823	4453	16.5
	-0.02	2793	3259	16.7	3917	4739	21.0
	-0.03	2902	3516	21.1	4019	4972	23.7
	-0.04	3016	3674	21.8	4360	5653	29.7
	-0.05	3145	4033	28.2	5181	6692	29.2
med util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3526	3512	-0.4	3928	4665	18.8
	-0.01	3041	3576	17.6	4075	4897	20.2
	-0.02	3068	3672	19.7	4370	5403	23.6
	-0.03	3087	4083	32.2	4595	5703	24.1
	-0.04	3203	4286	33.8	5288	6496	22.8
	-0.05	3669	4636	26.3	7097	8145	14.8
high util		α =0.05			α =0.1		
		MRP	RPS	Δ	MRP	RPS	Δ
β	0	3522	3885	10.3	4463	5163	15.7
	-0.01	3552	3961	11.5	4760	5491	15.4
	-0.02	3621	4093	13.0	5344	6023	12.7
	-0.03	3710	4309	16.1	5700	6337	11.2
	-0.04	3887	4550	17.1	6683	7458	11.6
	-0.05	4277	5078	18.7	8509	9478	11.4

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