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Smart Production Planning Model for T-Shirt Products at Raensa Convection

Sesar Husen Santosa[1a◆], Agung Prayudha Hidayat[1b], Ridwan Siskandar[2c], Khoirul Aziz Husyairi[3d]

Abstract. *The increasing stock condition of cotton combed 30s t-shirts causes Convection to require optimal production planning, influenced by demand, safety stock, and selling price. The analysis of forecasting demand for t-shirts obtained a need for 217 t-shirts using the Multiplicative Decomposition forecasting method with MAD = 22.47 and MAPE = 0.17. Based on demand data for 1 year, the Safety Stock that must be maintained is 126 shirts/month or 3 shirts/week. The optimal production defuzzification results are 369 t-shirts with 81 fuzzy rules used. The Master Production Planning (MPS) directs the production schedule to be carried out in January, scheduled for the 4th week of December the previous year, as many as 123 shirts and ended on the third Sunday in January as many as 92 shirts to maintain stock conditions and meet the demand of consumer.*

Keywords: *Forecasting, Safety Stock, Defuzzification, Master Production Schedule.*

I. INTRODUCTION

Demand uncertainty can affect consumer expectations of product purchases and production processes (Dev et al., 2020). Forecasting demand for consumer needs, the amount of Stock available in the company, and production costs for the number of products produced are critical factors in production planning decisions (Vieira et al., 2021).

Product demand must be optimized so resource requirements, including raw materials, can be identified optimally (Kück & Freitag, 2020). Demand forecasting determines production schedules and raw materials (Lohmer & Lasch, 2020).

Production planning must be based on consumer needs and stock conditions to optimize production scheduling (Díaz-madroñero & Mula, 2019). Optimal production planning can prevent stock buildup or shortages (Thürer et al., 2020). The production of cotton combed 30s t-shirts at the Raensa convection requires planning related to the demand, selling prices, and the amount of safety stock so that the amount of output and the amount of Stock in the warehouse is optimal. Demand forecasting, where fluctuating demand can affect optimal production levels (Santosa & Hidayat, 2019). Seasonal demand has a non-linear trend, so it must use a weighting index for each season (Yildirim et al., 2021)

Production costs and capacity will affect the optimal product price determination (Tang et al., 2021). Optimal price and production strategies will determine success in managing the company's supply chain (Yu et al., 2021).

Fluctuations in the number of requests will affect the amount of Stock, so it must be identified optimally (Bahroun & Belgacem, 2019). Production scheduling using demand forecasting must pay attention to errors because they will affect the amount of Stock (Kim et al., 2019). Optimal ordering will affect stock conditions, so every influencing variable must be analyzed in production activities (Santosa et al., 2021).

Demand, price, and safety stock conditions influence production scheduling at Raensa convection. This condition causes Convection to

[1] Industrial Management Study Program, College of Vocational Studies, IPB University, Bogor, 16128, Indonesia
[1] Computer Engineering Study Program, College of Vocational Studies, IPB University, Bogor, 16128, Indonesia
[1] Agribusiness Management Study Program, College of Vocational Studies, IPB University, Bogor, 16128, Indonesia

[a] email: sesarhusensantosa@apps.ipb.ac.id
[b] email: agungprayudha@apps.ipb.ac.id
[c] email: ridwansiskandar@apps.ipb.ac.id
[d] email: khoirulaziz@apps.ipb.ac.id
◆ corresponding author

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make optimal production scheduling by considering the three variables above.

Variables in production planning can have fuzzy values and can be identified using a fuzzy logic approach so that each parameter value limit can be identified optimally (Khatua & Kar, 2019; Santosa et al., 2020). Fuzzy logic is used in decision making by using a vague value limit for each variable that affects the amount of production (Han et al., 2020; Santosa et al., 2022). Decision-making related to production scheduling must pay attention to integrated variables and influence each other (Bendul & Blunck, 2019; Dias & Ierapetritou, 2019).

Production scheduling at Raensa Convection must use a scheduling method to identify stock conditions based on consumer demand. Master Production Schedule (MPS) is used in planning production schedules based on consumer demand conditions, customer orders, production lead times, and stock conditions (Mönch et al., 2018).

This research has a novelty in determining optimal production using a fuzzy logic approach by three influencing variables, seasonal demand, safety stock, and selling prices, which are integrated with the Master Planning Schedule (MPS).

II. RESEARCH METHOD

Production planning for cotton combed 30s t-shirts at Raensa Convection is integrated from demand planning, safety stock, optimal production using fuzzy logic, and Master Production Schedule (MPS). Optimal production scheduling planning integration using the following methods:

1. **Multiplicative Decomposition Forecasting Method**. Multiplicative Decomposition Forecasting is used to identify demand with seasonal types (Naimoli & Storti, 2019). This forecasting method uses a seasonal index based on the seasonal Period to identify future demand levels. The formulation of the forecasting model is as follows (Cheng et al., 2021):

   $Y_t = TR_t \times SN_t \times CL_4 \times IR_t$ (1)

   where

   Y_t = forecasting value in period t.
   TR_t = Linear trend in period t,
   SN_t = Seasonal index in period t,
   CL_t = Silical factor in period t,
   IR_t = Irregular factor in period t.

2. **Level of Accuracy of Forecasting Methods**. The accuracy level is measured by comparing the error values of several forecasting methods to get the right forecasting value (Huang & Hsieh, 2020). The level of accuracy used in forecasting is the Mean Absolute Deviation (MAD) and the Mean Absolute Percentage Error (MAPE) as follows (Jiang et al., 2021):

   $$\text{MAD} = |\text{Forecast Result} - \text{Demand}| \quad (2)$$

   $$\text{MPE} = \sum_{i=1}^{m} \{\left[\frac{|\text{Error}|}{\text{Demand}}\right] /\text{Period}\} \quad (3)$$

3. **Safety Stock Model**. Safety stock is a stock condition that must be maintained for a certain period to meet fluctuating demand optimally. This method determines ideal stock limits based on consumer demand (Yao & Qin, 2020). The calculation of safety stock is as follows: (Lee, 2019)

   $$\text{Safety Stock} = (Z\alpha \times \pi d \times \sqrt{\text{Lead time}}) \quad (4)$$

   $$\text{ROP} = (\text{Average daily demand} \times \text{Lead time}) + (Z\alpha \times \pi d \times \sqrt{\text{Lead time}}) \quad (5)$$

4. **Fuzzy Membership Association.** The fuzzy membership set determines the parameter value limits of the optimal stock demand, price, and production variables. The triangular membership set is used when the variable has only one highest degree value, and the Trapezoidal membership set is used when the variable has parameters that have more than one degree of membership (Hu et al., 2019; Zohoori et al., 2018).
5. **Defuzzification.** The defuzzification process determines optimal production as a basis for making Master Production Planning (MPS). The Center of Area (COA) method is used to determine the moment and area based on the parameter values that occur for each variable (Jayetileke & Mel, 2022). The Center of Area

method is as follows (Pourjavad & Shahin, 2018):

$$\text{Defuzzyficaton} = \frac{\int_{b=0}^{a} \mu A(a)x \, dx}{\int_{b=0}^{n} \mu A(a) \, dx} \quad (6)$$

6. **Master Production Schedule.** The cotton combed 30s t-shirt production scheduling is based on the Gross Requirement value of determining the optimal amount of production in the defuzzification process using the COA method. The Master Production Schedule (MPS) method is used based on the results of determining the optimal output, which will be used as gross requirements (Vargas & Metters, 2011). Determination of MPS is done by identifying Gross Requirements, Customer Orders, Inventory On Hand, and production lead times so that the products produced meet the production targets set by the company (Englberger et al., 2016).

III. Result and Discussion

They forecast the demand for the T-Shirt with cotton combed 30s materials in Convection using demand data for one year. Demand data has a seasonal trend where the market fluctuates. Clothing demand data can be seen in Table 1.

Table 1. Demand T-Shirt in 2022

Month	Demand	Month	Demand
January	145	July	90
February	90	August	135
March	125	September	240
April	110	October	85
May	265	November	115
June	110	December	80

Based on the demand for T-Shirt cotton combed in the 30s for one year, the demand trend is seasonal, divided into four seasonal periods. Forecasting that can identify requests with seasonal data types using the Multiplicative Decomposition method using the POM Windows application. The results of forecasting the demand for t-shirts can be seen in Figure 1.

The results of demand forecasting by dividing the seasonal index for four periods show that trend forecasting is demand (y) = 132.068 + 0.07 time. Based on the trend value, the seasonal factor value for the four seasonal periods is 1.64, 0.72, 0.83, and 0.82. Based on the seasonal factor value, the forecast for the demand for t-shirts in the 13th month or January of the following year is

Forecasting Results

(untitled) Summary

Measure	Value	Future Period	Unadjusted Forecast	Seasonal Factor	Adjusted Forecast
Error Measures		13	132,93	1,64	217,38
Bias (Mean Error)	,02	14	133	,72	95,36
MAD (Mean Absolute Deviation)	22,47	15	133,07	,83	110,47
MSE (Mean Squared Error)	872,55	16	133,13	,82	108,85
Standard Error (denom=n-2-4=6)	41,77	17	133,2	1,64	217,81
MAPE (Mean Absolute Percent Error)	,17	18	133,27	,72	95,55
Regression line (unadjusted forecast)		19	133,33	,83	110,69
Demand(y) = 132.0663		20	133,4	,82	109,07
+ ,07 * time		21	133,47	1,64	218,25
Statistics		22	133,53	,72	95,74
Correlation coefficient	,86	23	133,6	,83	110,91
Coefficient of determination (r^2)	,73	24	133,67	,82	109,29
		25	133,73	1,64	218,68
		26	133,8	,72	95,93

Figure 1. T-Shirt Forecast Result

Table 2. Error Accuracy Level Analysis

Month	Demand	Forecast Result	Error	|Error|	|Error|^2	Percentage Error
January	145	216,07	-71,07	71,07	5050,94	0,49
February	90	94,78	-4,78	4,78	22,85	0,05
March	125	109,81	15,19	15,19	230,74	0,12
April	110	108,20	1,80	1,80	3,24	0,02
May	265	216,50	48,50	48,50	2352,25	0,18
June	110	94,98	15,02	15,02	225,60	0,14
July	90	110,03	-20,03	20,03	401,20	0,22
August	135	108,42	26,58	26,58	706,50	0,20
September	240	216,94	23,06	23,06	531,76	0,10
October	85	95,17	-10,17	10,17	103,43	0,12
November	115	110,25	4,75	4,75	22,56	0,04
December	80	108,63	-28,63	28,63	819,68	0,36

217 t-shirts.

Based on the results of the forecasting, then the value of the accuracy of the forecast results is determined using the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) values. The results of the analysis of the accuracy of the error can be seen in Table 2.

Based on the analysis of the level of forecasting accuracy, the MAD value = 22.47 and MAPE = 0.17. This level of accuracy indicates that the results of forecasting the demand for T-shirts were 217 T-shirts in January of the following year with a MAPE value below 0.2.

Based on the t-shirt demand data, an analysis is carried out related to the planning of Safety Stock which must be maintained at the Convection to meet the fluctuating demand for t-shirts. Based on production demand and lead time for four days and using a Confidence Level value = 90%. Based on the confidence level, the value of $Z\alpha$ = 1,28 is obtained so that the Safety Stock and Reorder Point (ROP) for one year is obtained as follows:

Safety Stock = (1,28 x 57,209 x √4)
= 146 T-Shirt/Year

ROP = (133 x 4) + (1,28 x 133 x √4)
= 676 T-Shirt/Year

The results of the safety stock calculation show that Convection must have 146 t-shirts/per year. Based on this data, every week, the Safety Stock that must be maintained is three t-shirts to avoid Stock and Stock out due to fluctuations in demand.

Based on the demand, safety stock, and selling price analysis, Convection must determine the ideal product to be carried out. The three variables that affect decision making regarding the optimal production quantity have different parameter limits, so they have fuzzy values that can be analyzed using a fuzzy logic approach. The set of fuzzy memberships based on actual

Table 3. Fuzzy Membership Function

Variable	Low	Medium	High
Demand	100; 100; 250; 400	350; 450; 550	500; 650; 800; 800
Safety Stock	5; 15; 25	20; 35; 50	45; 65; 85
Price (x 1000)	40; 50; 60	55; 65; 75	65; 75; 85
Optimal Production	0; 120; 240	200; 400; 600	500; 610; 720

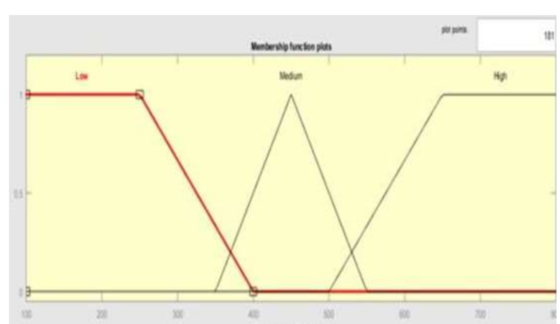

Figure 2. Demand Membership Function

convection conditions can be seen in Table 3.

Based on the membership set parameters above, the graph of the membership function request for t-shirts can be seen in Figure 4.

The following variable that affects the determination of optimal orders is safety stock. The membership set of the safety stock variables can be seen in Figure 5. The price variable for t-shirts is one of the variables influencing decision making regarding optimal t-shirt production. Price membership sets can be seen in Figure 6.

The defuzzification process is carried out by determining the fuzzy membership set, namely

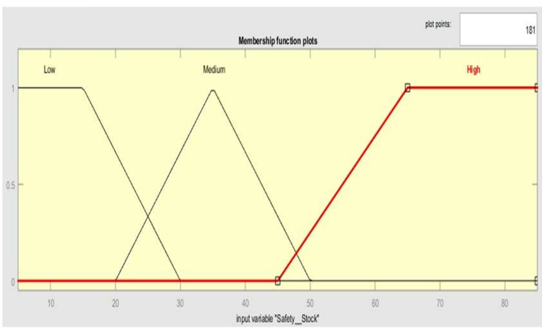

Figure 3. Safety Stock Membership Function

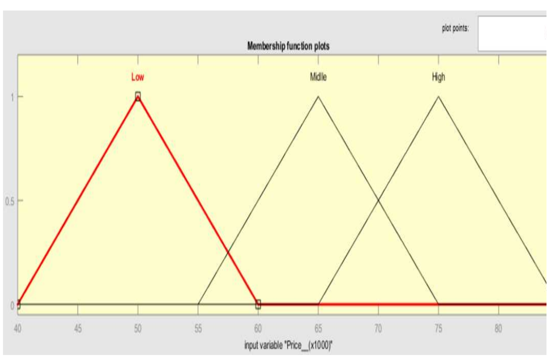

Figure 4. Selling Price Membership Function

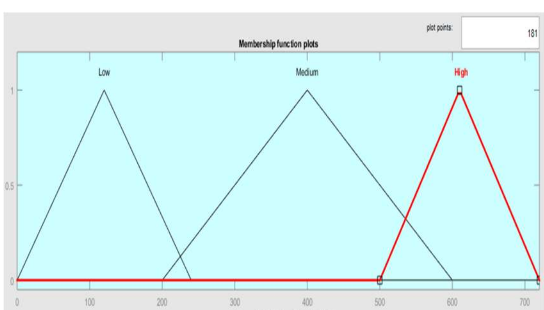

Figure 5. Optimal Order Membership Function

the optimal order. The optimal t-shirt production membership set can be seen in Figure 7.

The fuzzy rules can be determined based on the input and output membership sets. There are 81 fuzzy rules-based applications, as seen in Figure 8.

Based on the number of demand forecasts for 217 t-shirts, a safety stock of 12 t-shirts/month, and a selling price of IDR 62,500/shirt, a fuzzy operator can be determined, which will be used in the defuzzification process. Based on the parameter values, the fuzzy operator (α) is obtained, namely:

α = Min (μ_{demand} [0,94] ∩ μ_{Price} [0,75] ∩ $\mu\_{Safety\ Stock}$ [0,7])

α = Min (0,94; 0,75 0,7)

α = 0,7

Based on the fuzzy operator (α), the moment and the area used in the optimal production defuzzification process can be determined. The moments that occur based on the parameter values for each variable are as follows:

$$\text{Moment 1}: \int_0^{70} 0{,}01x2\ dx$$

$$\text{Moment 2}: \int_{70}^{156} 0{,}7x\ dx$$

$$\text{Moment 3}: \int_{156}^{240} 2x - 0{,}083x2\ dx$$

$$\text{Moment 4}: \int_{200}^{340} 0{,}005x - x\ dx$$

$$\text{Moment 5}: \int_{340}^{460} 0{,}7x\ dx$$

$$\text{Moment 6}: \int_{460}^{600} 3x - 0{,}005x2\ dx$$

$$\text{Moment 7}: \int_{500}^{577} 0{,}01x2 - 5x\ dx$$

$$\text{Moment 8}: \int_{577}^{643} 0{,}7x\ dx$$

$$\text{Moment 9}: \int_{643}^{720} 6x - 0{,}01x2\ dx$$

The area used in the optimal production defuzzification process can be determined based on the fuzzy operator values. The area obtained is as follows:

Area 1 = $\frac{(70-0)\ x\ 0{,}7}{2} = 24{,}5$

Area 2 = (156-70) x 0,7 = 60,2

Area 3 = $\frac{(240-15\ \ )\ x\ 0{,}7}{2} = 29{,}4$

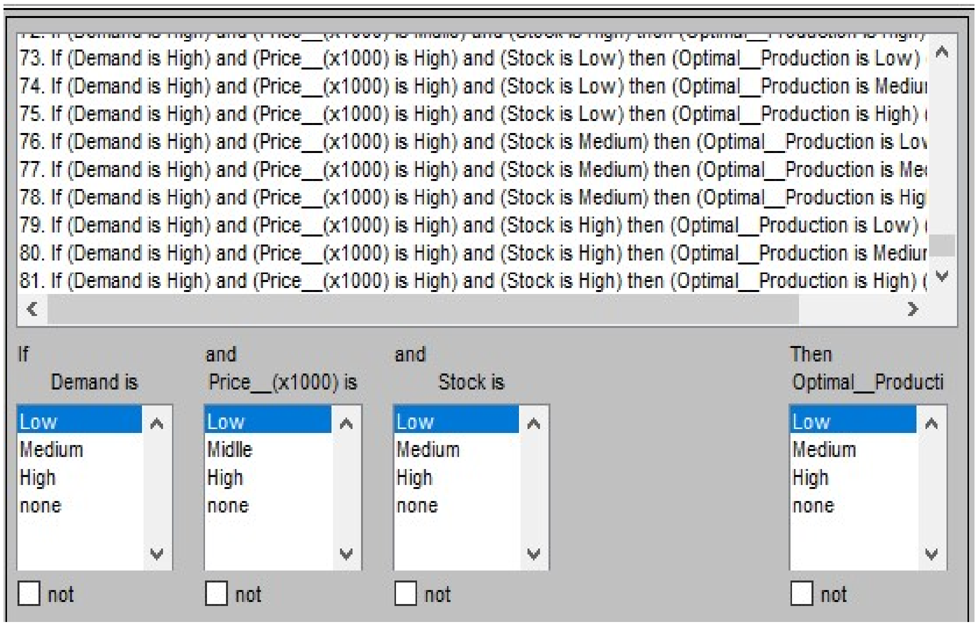

Figure 6. Fuzzy Rule Base

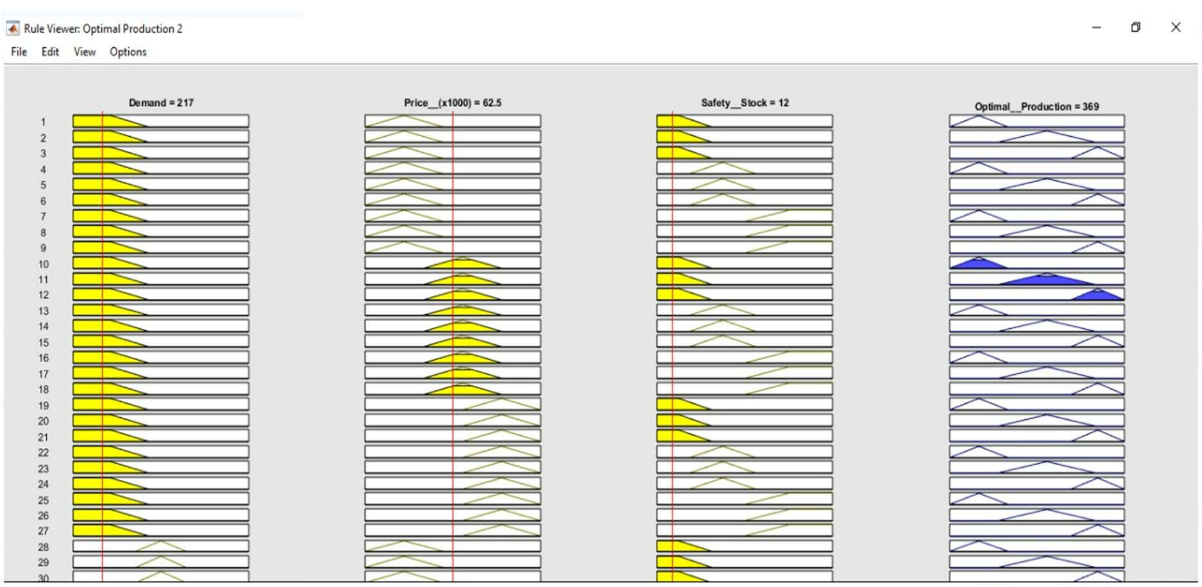

Figure 7. Defuzzification Optimal Production

Area 4 = $\frac{(340-200) \text{ x } 0{,}7}{2}$ = 49

Area 5 = (460-340) x 0,7 = 42

Area 6 = $\frac{(600-460) \text{ x } 0{,}7}{2}$ = 49

Area 7 = $\frac{(577-500) \text{ x } 0{,}7}{2}$ = 26,95

Area 8 = (643-550) x 0,7 = 65,1

Area 9 = $\frac{(720-6\quad) \text{ x } 0{,}7}{2}$ = 26,95

Based on the actual moment of 137673.89 and the area value of 373.1, the optimal production defuzzification process is carried out using the Center of Area (COA) method. The optimal production defuzzification results using the Matlab application can be seen in Figure 9.

The results of optimal order defuzzification of 369 t-shirts will be used as Gross Requirements in Master Production Planning (MPS). Production scheduling using Master Production Planning

(MPS) is based on gross requirements, customer orders, inventory on hand, safety stock, and production lead time. Master Production Schedule for cotton combed 30s T-shirts at Raensa Convection based on the results of defuzzification of optimal t-shirt production with a production lead time of 1 week and a safety stock of 3 t-shirts/week seen in Table 4.

Tabel 4. Master Production Schedule T-Shirt

Component	Period				
	4	1	2	3	4
Gross Requirement		92	92	92	92
Customer Order		120	0	95	0
Inventory On Hand		-120	-89	-92	-89
JIP-Receipts		123	92	95	92
JIP-Schedule	123	92	95	92	

Based on the production scheduling plan above, Convection must produce 123 T-shirts in the 4th week of December and end in the 3rd week of January with 92 T-shirts to achieve the one-month production target.

Demand, safety stock, and prices influence the production planning for t-shirts at the Raensa convection. These three variables form the basis for making decisions related to production planning. Aggregate planning is carried out to determine production cost efficiency based on demand [32]. The aggregate planning method for determining the production schedule only identifies one variable: consumer demand. It cannot identify the three critical variables for optimal production planning in Convection.

IV. Conclusion

Based on the results of forecasting using the Multiplicative Decomposition method, the forecasting shirts were 217 shirts with MAD = 22.47 and MAPE = 0.17. Safety stock that must be maintained in the Convection is 146 shirts/month or 3 shirts/week. The results of defuzzification based on demand forecasting, safety stock, and selling prices obtained an optimal production of 369 t-shirts/month. The January production schedule starts on the 4th week of December the previous year with 123 shirts until the 3rd week of January with 92 shirts. The following research must be carried out to develop a raw material planning model based on supplier's availability so that the production schedule can run optimally.

References

Bahroun, Z., & Belgacem, N. (2019). Determination of dynamic safety stocks for cyclic production schedules. 2, 62–93.

Bendul, J. C., & Blunck, H. (2019). Computers in Industry The design space of production planning and control for industry 4.0. *Computers in Industry, 105*, 260–272. https://doi.org/10.1016/j.compind.2018.10.010

Cheng, M. L., Chu, C. W., & Hsu, H. L. (2021). A study of univariate forecasting methods for crude oil price. Maritime Business Review. https://doi.org/10.1108/MABR-09-2021-0076

Dev, N. K., Shankar, R., & Swami, S. (2020). Diffusion of green products in industry 4.0: Reverse logistics issues during design of inventory and production planning system. International Journal of Production Economics, 223. https://doi.org/10.1016/j.ijpe.2019.107519

Dias, L. S., & Ierapetritou, M. G. (2019). Data - driven feasibility analysis for the integration of planning and scheduling problems. In Optimization and Engineering (Issue 0123456789). Springer US. https://doi.org/10.1007/s11081-019-09459-w

Díaz-madroñero, A. G. M. M., & Mula, J. (2019). Master production schedule using robust optimization approaches in an automobile second-tier supplier. Central European Journal of Operations Research. https://doi.org/10.1007/s10100-019-00607-2

Englberger, J., Herrmann, F., & Manitz, M. (2016). Two-stage stochastic master production scheduling under demand uncertainty in a rolling planning environment. 7543(April). https://doi.org/10.1080/00207543.2016.1162917

Han, J., Liu, Y., Luo, L., & Mao, M. (2020). Jou. Knowledge-Based Systems, 106056. https://doi.org/10.1016/j.knosys.2020.106056

Hu, G., Bakhtavar, E., Hewage, K., Mohseni, M., & Sadiq, R. (2019). Heavy metals risk assessment in drinking water: An integrated probabilistic-fuzzy approach. Journal of Environmental Management, 250(September), 109514. https://doi.org/10.1016/j.jenvman.2019.109514

Huang, C. H., & Hsieh, S. H. (2020). Predicting BIM labor cost with random forest and simple linear regression. Automation in Construction, 118 (December 2019), 103280.

https://doi.org/10.1016/j.autcon.2020.103280

Jayetileke, H. R., & Mel, W. R. De. (2022). applied sciences Real-Time Metaheuristic Algorithm for Dynamic Fuzzification , De-Fuzzification and Fuzzy Reasoning Processes.

Jiang, P., Liu, Z., Niu, X., & Zhang, L. (2021). A combined forecasting system based on statistical method, artificial neural networks, and deep learning methods for short-term wind speed forecasting. Energy, 217, 119361. https://doi.org/10.1016/j.energy.2020.119361

Khatua, D., & Kar, K. M. S. (2019). A Fuzzy Optimal Control Inventory Model of Product – Process Innovation and Fuzzy Learning Effect in Finite Time Horizon. International Journal of Fuzzy Systems, 21(5), 1560–1570. https://doi.org/10.1007/s40815-019-00659-1

Kim, S., Kim, H., & Lu, J. (2019). A practical approach to measuring the impacts of stockouts on demand. 4(February), 891–901. https://doi.org/10.1108/JBIM-04-2018-0126

Kück, M., & Freitag, M. (2020). Jou rna. International Journal of Production Economics, 107837. https://doi.org/10.1016/j.ijpe.2020.107837

Lee, C. (2019). A Mathematical Safety Stock Model for DDMRP Inventory Replenishment. 2019.

Lohmer, J., & Lasch, R. (2020). Production planning and scheduling in multi- factory production networks : a systematic literature review systematic literature review. International Journal of Production Research, 0(0), 1–27. https://doi.org/10.1080/00207543.2020.1797207

Mönch, L., Uzsoy, R., & Fowler, J. W. (2018). A survey of semiconductor supply chain models part III : master planning , production planning , and demand fulfilment. International Journal of Production Research, 7543, 1–20. https://doi.org/10.1080/00207543.2017.1401234

Naimoli, A., & Storti, G. (2019). Heterogeneous component multiplicative error models for forecasting trading volumes. International Journal of Forecasting, 35(4), 1332–1355. https://doi.org/10.1016/j.ijforecast.2019.06.002

Pourjavad, E., & Shahin, A. (2018). The Application of Mamdani Fuzzy Inference System in Evaluating Green Supply Chain Management Performance. International Journal of Fuzzy Systems, 20(3), 901–912. https://doi.org/10.1007/s40815-017-0378-y

Santosa, S. H., & Hidayat, A. P. (2019). Model Penentuan Jumlah Pesanan Pada Aktifitas Supply Chain Telur Ayam Menggunakan Fuzzy Logic. Jurnal Ilmiah Teknik Industri, 18(2), 224–235. https://doi.org/10.23917/jiti.v18i2.8486

Santosa, S. H., Hidayat, A. P., & Siskandar, R. (2021). Safea application design on determining the optimal order quantity of chicken eggs based on fuzzy logic. IAES International Journal of Artificial Intelligence, 10(4), 858–871. https://doi.org/10.11591/ijai.v10.i4.pp858-871

Santosa, S. H., Hidayat, A. P., & Siskandar, R. (2022). Raw material planning for tapioca flour production based on fuzzy logic approach: a case study. Jurnal Sistem Dan Manajemen Industri, 6(1), 67–76. https://e-jurnal.lppmunsera.org/index.php/JSMI/article/view/4594

Santosa, S. H., Sulaeman, S., Hidayat, A. P., & Ardani, I. (2020). Fuzzy Logic Approach to Determine the Optimum Nugget Production Capacity. Jurnal Ilmiah Teknik Industri, 19(1), 70–83. https://doi.org/10.23917/jiti.v19i1.10295

Tang, X., He, Y., & Salling, M. (2021). International Journal of Production Economics Optimal pricing and production strategies for two manufacturers with industrial symbiosis. International Journal of Production Economics, 235(June 2020), 108084. https://doi.org/10.1016/j.ijpe.2021.108084

Thürer, M., Fernandes, N. O., & Stevenson, M. (2020). Production planning and control in multi-stage assembly systems : an assessment of Kanban , MRP , OPT (DBR) and DDMRP by simulation. International Journal of Production Research, 0(0), 1–15. https://doi.org/10.1080/00207543.2020.1849847

Vargas, V., & Metters, R. (2011). Int . J . Production Economics A master production scheduling procedure for stochastic demand and rolling planning horizons. Intern. Journal of Production Economics, 132(2), 296–302. https://doi.org/10.1016/j.ijpe.2011.04.025

Vieira, M., Moniz, S., Gonçalves, B. S., Pinto-varela, T., Barbosa-póvoa, P., Neto, P., Vieira, M., Moniz, S., Gonçalves, B. S., & Pinto-varela, T. (2021). A two-level optimisation-simulation method for production planning and scheduling : the industrial case of a human – robot collaborative assembly line. https://doi.org/10.1080/00207543.2021.1906461

Yao, K., & Qin, Z. (2020). Barrier option pricing formulas of an uncertain stock model. Fuzzy Optimization and Decision Making. https://doi.org/10.1007/s10700-020-09333-w

Yildirim, A. N., Bas, E., & Egrioglu, E. (2021). Threshold single multiplicative neuron artificial neural networks for non-linear time series forecasting ABSTRACT.

https://doi.org/10.1080/02664763.2020.1869702

Yu, Y., Zhou, D., Zha, D., Wang, Q., & Zhu, Q. (2021). Optimal production and pricing strategies in auto supply chain when dual credit policy is substituted for subsidy policy. 226. https://doi.org/10.1016/j.energy.2021.120369

Zohoori, B., Verbraeck, A., Bagherpour, M., & Khakdaman, M. (2018). Monitoring production time and cost performance by combining earned value analysis and adaptive fuzzy control. Computers & Industrial Engineering. https://doi.org/10.1016/j.cie.2018.11.019