JURNAL ILMIAH TEKNIK INDUSTRI
ISSN: 1412-6869 (Print), ISSN: 2460-4038 (Online)
Journal homepage: http://journals.ums.ac.id/index.php/jiti/index
doi: 10.23917/jiti.v22i1.20115

Robust Multi-Objective Optimization Model for the Integration of Blood Production and Distribution Planning

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Abstract. *Blood is a very important element for humans. Currently, The Blood Transfusion Unit of The Indonesian Red Cross in City "X" determines the amount and type of blood to be processed based on stock availability. This method tends to be subjective so that the possibility of error in production decision is fairly high. This research intends to manage that the blood processing process and allocation can be carried out optimally and on target. The research objectives are to minimize the number of blood shortages, expired blood, and the total costs incurred, by applying a robust optimization method that considers the uncertainty of blood demand and the disturbances in the blood production process. Pass data of demands will be used for forecasting demand in the planning period. The forecast results can be adjusted to current conditions using the adjustment ratios. The robust optimization method can produce decisions that tend to be stable even when there are changes in blood demand. The results obtained in this study were 24% decrease in the number of shortages of blood stock, 88% decrease in the amount of expired blood, and 96% decrease in the overproduction cost.*

Keywords: *blood production and distribution; multi-objective; pre-emptive goal programming; robust optimization.*

I. INTRODUCTION

Planning the production and distribution process of blood is very important since blood is an important and critical element for human life. In the midst of the COVID-19 pandemic, there has been a decline in the number of donors who are willing and qualified to donate blood. The Blood Transfusion Unit of The Indonesian Red Cross (BTU-IRC) in City "X" determines the amount and type of blood to be produced based on the number of depleting stocks. This method tends to be subjective so that the possibility of production error is high. The Government Regulation Number 7 Year 2011 stated that blood can only be issued by BTU-IRC, and there is no transfer of blood between hospital blood banks. In 2020, there was 0.9% of the total production of red cell type blood that was expired and had to be destroyed due to overproduction. It is therefore necessary to integrate blood production and distribution planning so that blood supply can be accurate and efficient.

Blood obtained from donors is still in the form of whole blood (whole blood). Some of the blood will still be stored as whole blood and some will be separated into several blood products. One of the results of the separation is packed red cell (PRC). There are two types of blood prepared from packed red cells (PRC), namely leukoreduced PRC (PCR) and leukodepleted PRC (PCLs). Both blood preparations were the result of leukocyte filtration from PRC, but the leukocyte content of leukodepleted PRC is lower than that of leukoreduced PRC. This blood type has a useful life of 35 days from the time it is received from the donor. Limitations of types and groups that cannot substitute freely with each other, storage age, storage conditions of blood, and most importantly the limited amount of blood supply make the problem of planning the production and distribution of blood more complex than other products.

This study aims to: (1) minimize the shortage of the required blood type stock by forecasting the demand for blood for each type and blood group every week, and (2) design an integration

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Submited: 18-10-2022 Revised: 26-05-2023
Accepted: 15-06-2023

of blood production and distribution planning using the robust multi-objective optimization to minimize the amount of shortage of blood stock, expired blood, and the total costs incurred by BTU-IRC City "X". In this study, only red cell types (packed red cell, leukoreduced packed red cell, and leukodepleted packed red cell) are discussed. The method used in this research is pre-emptive goal programming that works by the concept of prioritizing. Solving problems with this method will prioritize the achievement of the objective function with higher priority before processing the other objective functions with lower priority. The model is said robust because it considers elements of uncertainty especially in the data of demand and can still perform well and stable despite changes in some data parameters.

Blood products are very critical to sustain life. Obtaining blood from blood donors is not easy because donating blood is a voluntary activity. Blood products are perishable and their quality decrease rapidly over the transportation period. There are other products with similar nature such as agricultural products. However, compared to the latter, the availability of blood products is critical in a much shorter time span and it could mean life or death to someone. Therefore, the logistics and supply chain of blood products need to be carefully and precisely planned.

Despite its importance, research in blood transportation is few. The last literature review is dated a decade ago (Beliën & Forcé, 2012), citing nearly a hundred of articles classified based on the blood type, solution method (simulation, integer programming, etc.), hierarchical level of the blood banks, the problem type (inbound versus outbound), the data approach (stochastic versus deterministic), the optimization approach (exact versus heuristic), performance measures, and the case studies.

Current research on blood supply chain and logistics is quite diverse in terms of breadth and depth. Mishra et al. (2021) employed a qualitative study by means of survey to identify factors affecting good inventory management of blood which put staff training at the top of the list, followed by managerial practices such as stringent allocation policy, diligent record-keeping, daily stock review, monthly performance reports, preventive maintenance of equipment, robust blood bank information system, communication with stakeholders, and effective leadership. Other qualitative research deals with risk management for blood supply chain. These include Boonyanusith & Jittamai (2019) who used the House-of-Risk model in the risk assessment process to arrive at strategic recommendation that enhancing the collaboration is the most proactive action to manage risks in the blood supply chain, followed by information sharing, and demand and supply statistical analysis. The research, however, does not offer tactical or operational suggestions. In a similar vein, Cagliano et al. (2021) offered a comprehensive and structured approach to proactively identify and analyze logistics risks as well as define responses to improve blood bag traceability, focusing on hospital wards. The authors emphasized the needs for specific key performance indicators to enable an improved communication flow among actors that can uncover residual risks.

In the quantitative department, more diverse approaches are reported in the literature. Liu et al. (2020) applied one classical supply chain technique, vendor-managed inventory, in the scheduling of blood distribution. The authors proposed an integration of a decomposition-based algorithm with an adaptive large neighborhood search. Another classical application such as in location-allocation and inventory management is demonstrated by Hosseini-Motlagh et al. (2020). In this paper, the authors formulated a bi-objective two-stage stochastic programming model for managing a red-blood-cells supply chain to minimize the total cost of the supply chain which includes fixed costs, operating costs, inventory holding costs, wastage costs, and transportation costs along with minimizing the substitution levels to provide safer blood transfusion services. The model is said robust due to the inclusion of stochastic data and parameters (Bertsimas & Thiele, 2006).

In the wake of COVID-19 pandemic, a number of research appear stressing on the critical availability of blood products to help the health professionals battle the already-troublesome circumstances brought by the situation. For example, Ghasemi et al. (2022) focused on the distribution of blood plasma using the Stackelberg game theory technique and two-phase bi-level mixed integer linear programming (MILP) with the objectives to minimize the total costs and maximize the utility of donors. Plasma distribution was important back then during the period of vaccine unavailability. Another research is from Kenan & Diabat (2022) who discussed the shortages of blood donors due to social distancing and fear of leaving their homes during the pandemic, which resulted in disruption of blood supply chains. Using the two-stage stochastic programming where uncertainty of both demand and supply is considered, the authors suggested that bigger capacities of permanent collection facilities are favored over the mobility of temporary facilities, taking into account blood substitution and age-based demand, to reduce shortages significantly. Similar research is carried out by Khalilpourazari & Doulabi (2022), but in a slightly different scope and a different method, which is designing an emergency blood supply chain network design problem using a multi-objective Transportation-Location-Inventory-Routing (TLIR). Focusing on blood donors in blood supply chain, however, is not a new approach. Prior to the above three, Ramezanian & Behboodi (2017) have modeled a supply chain network design under uncertainties using a MILP formulation. They formed a utility function using parameters which include distance of blood donors from blood facilities, experience factor of donors in blood facilities, and advertising budget in blood facilities. In general, it is important to note that the logistics of blood products are in the category of crisis logistics which are not the same as ordinary logistics and require a different treatment (Razavi et al. 2020).

Other research worth mentioning given their uniqueness is as follows. Fallahi et al. (2021) designed a closed-loop blood supply chain network considering transportation flow and quality aspects. The closed-loop being considered was related to use of reusable blood transportation boxes. Last but not least, Meidute-Kavaliauskiene et al. (2022) and Hamadneh et al. (2021) discussed the importance of visibility in blood supply chain. The former proposed implementing blockchain to increase visibility and to achieve successful implementation of the blockchain, the involved parties must pass the first critical step in identifying and removing the barriers that hinder effective tracing of blood supply. The latter, using a case study in Scotland, argued that such visibility is important and plays a vital role for effective response to emergencies under demand and supply shortages.

This paper is different from the above research mainly in the method used. While some of the above cited research considered dual objectives, none of them considered more than two objectives. In this research, three objectives will be formulated and pre-emptive goal programming will be used to solve the three objectives following the set priorities. The model is a MILP which also considers uncertainties in some of the data. The model is said robust if its solution is still valid under varying circumstances such as change in some of the parameters.

II. RESEARCH METHOD

This research was conducted in several stages. The first stage was the collection of primary data (data on blood demand, the percentage of blood type production of red cells from the total blood production, the percentage of each blood group from the total demand, and data on blood acquisition) from BTU-IRC in City "X" and secondary data (data related to costs and distances between location) from various other sources.

The second stage was to perform data processing that would be used as input to the optimization model. The data processing carried out was the calculation and processing of cost data including several assumptions used, forecasting blood demand for each blood type, forecasting blood acquisition, and calculating the required safety stock. The cost data used in this study were operational costs, storage costs, expired blood costs, blood shortages costs, and transportation costs. Data on blood demand each month in the previous period were used to forecast blood demand. After forecasting the demand for blood, the forecasting results were adjusted to be more in line with the current conditions by using a multiplier, namely the adjustment ratios. These adjustment ratios could be changed depending on circumstances. The results of forecasting blood demand in months were divided into demand forecasting results in weeks because the optimization of blood production and distribution planning uses a weekly period. Monthly blood acquisition data in the previous period obtained were forecasted for the next period, then the results of the forecasting of blood collection were converted into units of weeks. In this study, safety stock was used to anticipate an increase in blood demand and avoid blood shortages. The amount of blood safety stock for each type and group was determined based on the results of the mean square deviation (MSD) error from forecasting using a service level of 98%.

The third stage was the development of an optimization model that fit with the conditions at BTU-IRC in City "X". After all the data had been processed, they were used as the parameters for the optimization process. The results of the optimization process in this study were compared to the actual data in BTU-IRC in City "X" under several assumptions due to some data limitation.

This study was conducted to integrate blood distribution and production planning in "X". The flow of blood starting from the collection can be seen on Figure 1.

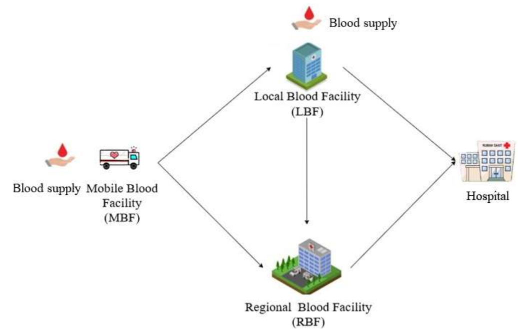

Figure 1. The process of blood transportation.

The blood is gathered from the blood collection at several locations of the mobile blood facility and BTU-IRC in City "X". All the blood obtained is processed at the BTU-IRC in City "X" and then stored in the BTU-IRC in City "X" storage. Every blood bank that needs blood should submit a request to BTU-IRC in City "X" (there are three types of blood storage locations, namely BTU-IRC in City "X", internal blood bank of BTU-IRC in City "X", and hospital blood bank) by considering the lifespan of the blood. If the blood has exceeded the lifespan, it is separated and categorized as expired blood which will then be destroyed. Patients who need blood transfusions can submit a request to the hospital blood bank and the internal blood bank of BTU-IRC in City "X".

The demand for blood in "X" is not always the same, and it varies from low, normal, and high. In this study, several demand scenarios and disruptions that can occur were used. There were several conditions in this study, namely:

- Blood production disruptions may happen at BTU-IRC in City "X".
- The number of vehicles owned by BTU-IRC in City "X" is limited.
- The type of blood given is always the same as the type of blood requested. If the stock is not available, it will be counted as shortage.
- Every location has its own storage facility.
- There is a blood shortage cost per bag which is calculated every time there is a blood shortage and wastage cost for every expired blood bag.
- The earlier stock of blood is used first according to the FIFO rules.
- There is only one lifespan of blood since the type of blood in this study has the same lifespan.

The indices are:

$j \in J$: represents the mobile blood facility
$h \in H$: represents the blood bank
$s \in S$: represents the demand scenario
$s' \in S'$: represents the disturbance scenario
$t \in T$: represents the periods

$r \in R$: represents the raw blood
$b \in B$: represents the blood type

The parameters are:

OL : Operational cost of blood treatment
HL : Storage cost at BTU-IRC in City "X"
HH : Storage cost at blood bank
WL_b : Excess cost for every type b blood bag at BTU-IRC in City "X"
WL_{bh} : Excess cost for every type b blood bag at blood bank
CL_b : Shortage cost for every type b blood bag at BTU-IRC in City "X"
CL_{bh} : Shortage cost for every type b blood bag at hospital blood bank
ML_j : Transport cost from mobile blood facility j to BTU-IRC in City "X"
LH_h : Transport cost from BTU-IRC in City "X" to blood bank h
MTC : The maximum capacity of the vehicles used
$CapL$: Storage capacity at BTU-IRC in City "X"
$CapH_h$: Storage capacity at blood bank h
N : The number of vehicles available at BTU-IRC in City "X"
LT : Blood lifespan
D^s_{bht} : The number of type b blood request at blood bank h during the t period
pd^s : Probability of demand scenario s
$pp^{s'}$: Probability of disruption scenario s'
AM_{rj} : The amount of blood type r supply at mobile blood facility j
AL_r : The amount of blood type r supply at BTU-IRC in City "X"
FW_{rt} : The number of whole blood r request during t period
$dis^{s'}$: Percentage of disruption s'
$I0_b$: The amount of initial type b blood inventory at BTU-IRC in City "X"
$I'0_{bh}$: The amount of initial type b blood inventory at blood bank h
$oa^{ss'}_{bt}$: The number of expired type b blood bags at BTU-IRC in City "X" during the initial LF period under the s and s' scenarios
$o'a^{ss'}_{bht}$: The amount of expired type b blood bag at blood bank h during the initial LF period under the s and s' scenarios

The decision variables are:

Z_{jt} : 1 if there is a blood draw at mobile blood facility j during the t period, 0 otherwise
$u^{ss'}_{ht}$: 1 if there is a blood transport from BTU-IRC in City "X" to blood bank h during the t period under the s and s' scenarios, 0 otherwise
$q^{ss'}_{bht}$: The number of type b blood bags taken from BTU-IRC in City "X" to blood bank h pada during the t period under the s and s' scenarios
$I^{ss'}_{bt}$: The amount of type b blood stock at BTU-IRC in City "X" during the t period under the s and s' scenarios
$I'^{ss'}_{bht}$: The amount of type b blood stock at blood bank h during the t period under the s and s' scenarios
$o^{ss'}_{bt}$: The number of expired type b blood bags at BTU-IRC in City "X" during t period t under the s and s' scenarios
$o''^{ss'}_{bht}$: The number of expired type b blood bags at blood bank h during t period t under the s dan s' scenarios
$e^{ss'}_{blt}$: The amount of type b blood processed at BTU-IRC in City "X" during the t period under the s and s'
$n^{ss'}_{bt}$: The number of shortages of type b blood at BTU-IRC in City "X" during the t period under the s and s' scenarios
$nn^{ss'}_{bht}$: The number of shortages of type b blood at blood bank h during the t period

The mathematical model is presented at the end of the paper and can be explained below.

The objective function (1) aims to minimize the number of blood shortages, the objective function (2) aims to minimize the amount of expired blood, and the third objective function (3) aims to minimize the total costs incurred. The total cost consists of several cost components, namely operational costs, storage costs, excess costs, transportation costs, and shortage costs. The cost components that make up the total cost cannot be obtained directly. The calculation of the cost components is given in equations (4)-(8). Additional constraints in the study are given in (9)-(24).

Constraint (9) limits the number of vehicles. Constraint (10) is to manage the blood processing from raw blood to the type of blood that will be distributed to all blood banks. Constraints (11)-(15) direct the amount of processing, shipping, and storage of blood. Constraints(16)-(19) are related to the expired blood. Constraints (20)-(22) are the storage capacity. Constraints (23)-(24) are the nature of decision variables.

Constraints (1)-(24) were run with each of the three objective functions separately. The optimal results were the minimum blood shortage, expired blood, and total cost. These results then underwent robustness test using a different set of objective functions.

The objective functions (25)-(27) are the combined objective functions of the gap between the combined optimization results and the optimization results from each scenario combination and the expected combined results. The calculation of each component in the objective functions (25)-(27) is obtained from equations (28)-(30) and constraints (31)-(33). Equations (34)-(41) are the formulas for fuzzy interactive. These can be broken down as follows. Equations (34)-(36) are used to obtain a negative ideal solution for each objective function. Equation (37) is used to calculate $\mu_i(x)$ which is the fuzzy membership value of each objective function (in the range of 0 to 1). The higher the value of fuzzy membership, the better. The objective function (38) is the objective function to maximize all fuzzy membership values. Constraint (39) is to find the lowest fuzzy membership value from the three fuzzy membership values to be maximized. Constraint (40) aims to run all the previous constraints except the objective function. Constraint (41) is to keep the value of τ_0 between 0 to 1.

The preceding model was run in Lingo. The model in (1)-(24) was run first for each combination of demand and disruption scenarios using pre-emptive goal programming, i.e. the first objective function was executed first and then the results became constraints for solving the second objective function, and likewise, the results in the second optimization became the constraints for the third optimization process for the third objective function. These steps were repeated six times because there were six different combinations of demand and disruption scenarios.

The output from each combination of scenarios was used to test the robustness of the results. To run the robustness test, a different set objective functions were used, which are (25)-(27), added with (28)-(30) and constraints (31)-(33). The three objective functions were executed one by one and repeated three times because there were three main objective functions. The minimum values from running three by three objective functions became the positive ideal solution whereas the maximum values became the negative ideal solution.

Both the positive and negative ideal solutions were used to run the objective function (38) which aims to maximize the fuzzy membership value of the entire objective function. The purpose of using this method was to find the best results that can be obtained by the three objective functions.

III. Result and Discussion

Data on demand for red cells blood type (PRC, PCR, and PCLs) every month in 2019-2020 were used to forecast demand in the next period. Before determining the forecasting method to be used, it was necessary to plot the data first to find out the shape of the demand pattern in the previous period. The method used to forecast the demand for each blood type shown in Table 1.

Table 1. Forecasting method of demand for each type of blood

Type of blood	Forecasting method
PRC	Trend analysis (linear)
PCR	Seasonal variation with trend using additive model
PCLs	Seasonal variation with trend using additive model

The selected forecasting method was based on the demand pattern and the lowest mean square deviation (MSD). Here, the adjustment ratio was used as a multiplier. This adjustment ratio was used to adjust the results of demand forecasting to current conditions. The results of the adjustment for forecasting blood demand were still in the form of forecasting data for each type of blood (PRC, PCR, and PCLs) which were divided for each blood group using the percentage of demand data for each blood type in 2020. The results of forecasting blood demand for each type and blood type are given in Table 2.

Forecasting results in months were converted into weeks because production and distribution planning were carried out every week. The conversion of forecasting results into week time units was carried out using the coefficient of variance approach. The variation in weekly demand was higher than the variation in monthly demand, so the coefficient of variance in monthly demand in 2020 was used to determine the coefficient of variance every week.

Blood collection data from various blood donation locations were forecasted based on blood collection data in 2020. The method used to forecast the collection of blood demand in 2021 can be seen in Table 3 and the forecast results for each blood type are in Table 4.

The blood collection was reduced by the amount of blood that remains whole blood and was not processed into PRC, PCR, and PCLs. The amount of blood that remained whole blood was obtained by forecasting the demand based on 2020 data. The results of forecasting the demand for whole blood type for each blood group is shown in Table 5.

Blood demand at BTU-IRC in City "X" varies in each period and not all estimations of the increase or decrease in blood demand can be estimated by forecasting the demand. Therefore, several variations of demand scenarios and safety stock were used in this study. Safety stock is the minimum number of blood bags that must always be available to avoid a shortage of blood stock when there is a surge in demand. Calculation of the number of safety stock was obtained with the help of MSD error results for each forecasting of blood demand. Safety stock for each blood type can be seen in Table 6.

After all the required data is available, then the data were used as input in the optimization process using the objective functions and constraints that had been described previously for 8 weekly periods. In this study, three variations of demand scenarios (low, medium (normal) and high demand) and two types of disruption scenarios (production failure and screening) had their respective probabilities. The data for the medium demand scenario was forecasted data, while the data for the low demand scenario was obtained by lowering the medium demand scenario data by 20% and the data for the high demand scenario was obtained by adding 20% of the medium demand scenario data. Each

Table 2. Forecasting results of blood demand

Month	Type	23%	27%	9%	41%
		Type A (bag)	Type B (bag)	Type AB (bag)	Type O (bag)
Jan. 2021	PRC	1,449	1,716	576	2,579
	PCR	125	148	50	222
	PCLs	66	78	26	117
Feb. 2021	PRC	1,506	1,783	598	2,680
	PCR	150	178	60	267
	PCLs	60	71	24	107

Table 3. Blood collection forecasting method

Blood type	Forecasting method
A	Seasonal variation with trend using additive model
B	Seasonal variation with trend using additive model
AB	Trend analysis (linear)
O	Seasonal variation with trend using additive model

Table 4. Results of blood collection forecast

Month	Type A (bag)	Type B (bag)	Type AB (bag)	Type O (bag)
Jan. 2021	1,853	2,531	656	3,317
Feb. 2021	2,124	2,985	680	3,954

Table 5. Whole blood demand forecast

Month	23%	27%	9%	41%
	Type A (bag)	Type B (bag)	Type AB (bag)	Type O (bag)
Jan. 2021	197	233	78	351
Feb. 2021	178	211	71	317

combination of demand and disturbance scenarios was run to obtain the optimization results of the objective function of each combination, namely minimizing blood shortage, expired blood, and total cost. The results of these optimizations were used to run a combined optimization of all scenarios. The results of minimizing blood shortage, expired blood, and total cost as the objective function of this combined optimization were the expectation of a shortage of 624 bags of blood stock, 16 bags of expired blood, and the expected total cost of Rp6,156,731,323. This total cost consisted of operational costs for blood processing, blood storage costs, expired blood costs, blood transportation costs, and fees charged whenever there was a shortage of blood stock. From the results of this optimization, it can also be seen that the expected number of blood processing was 15,948 bags, the expected number of blood storage in BTU-IRC in City "X" was 11,714 bags, and the expected number of blood storage in all blood banks was 3,510 bags.

Table 6. Safety stock for each blood type

Blood type	Number of safety stock (bag)		
	Low Demand Scenario	Medium Demand Scenario	High Demand Scenario
A PRC	104	138	173
A PCR	81	108	135
A PCLs	51	68	85
B PRC	113	150	188
B PCR	88	117	146
B PCLs	56	74	93
AB PRC	65	87	109
AB PCR	51	68	85
AB PCLs	32	43	54
O PRC	138	184	230
O PCR	107	143	179
O PCLs	68	90	113

The results of the optimization in the study were compared with the actual conditions at BTU-IRC in City "X". Compared output includes the number of blood shortages, expired blood, blood production or processing, the cost of taking blood from various locations, the cost of sending blood to each blood bank, and the costs due to excess blood production. All differences between the data on blood requests and blood donations at BTU-IRC in City "X" City were counted as blood shortages. The comparison is shown in Table 7.

Table 7. Comparison of optimization results and actual condition

Variable	Optimization	Actual	% Change
Blood shortage (bag)	634	834	-24%
Expired blood (bag)	16	128	-88%
Production number (bag)	15,948	14,170	13%
Blood collection cost (Rp)	822,152	656,799	25%
Blood transportation cost (Rp)	1,011,947	NA	NA
Over production cost (Rp)	878,099	23,056,281	-96%

The number of blood shortages in the actual condition was 834 bags, and it was obtained with the assumption that all differences between blood demand and blood supply were categorized as shortage. The amount of expired blood in actual conditions was obtained from the percentage of expired blood in 2020 that as much as 0.9% of the total blood production was not used until it had passed its lifespan, so it had to be destroyed. The decrease in the number of blood shortages in the proposed model was 23.98% and the number of expired blood was 87.50%.

The amount of blood production in the proposed model was higher than the actual condition due to the higher demand forecasting results than the actual demand, but the number of blood shortages that occurred in the proposed model was lower. The cost of taking blood in the proposed model was known from the optimization results, while the cost of taking blood in actual conditions was obtained with the assumption that each blood collection location was only visited once per month. The cost of sending blood was the cost for sending blood to all hospital blood banks. In actual conditions, it was not possible to know the cost of sending blood due to the limited data obtained. The cost of excess blood production was the cost that arose when the blood that had been produced was not used until it was expired and had to be destroyed.

IV. Conclusion

The optimization model proposed in this study is a robust multi-objective optimization model that aims to minimize the number of blood shortages, the amount of expired blood, and the total costs incurred by considering the uncertainty of demand and disruption factors in the blood processing process. By forecasting blood demand, the results of blood production decisions become more precise, so that the number of shortages and expiration of blood is lower. In the proposed model, there was a decrease in the number of blood shortages by 23.89% and a decrease in the amount of expired blood by 87.5%. With the application of the robust optimization method, the Indonesian Red Cross Blood Transfusion Unit Surabaya can make decisions related to blood production and distribution planning. In addition, from this proposed model, the expected number of blood shortages, excess blood, and the total costs incurred can be estimated. However, in this study there were several assumptions used due to data limitations. In addition, the proposed model in this study did not cover all blood types. Therefore, for further research, it is recommended to complete any required data so that the results obtained are more precise and develop models

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$$Min\ Z_1 = \sum_{s'}\sum_{s} pd^{s} \cdot pp^{s'}(n_{bt}^{ss'} + \sum_{h} nn_{bht}^{ss'}) \tag{1}$$

$$Min\ Z_2 = \sum_{s'}\sum_{s} pd^{s} \cdot pp^{s'}(o_{bt}^{ss'} + \sum_{h} o'^{ss'}_{bht}) \tag{2}$$

$$Min\ Z_3 = \sum_{S'}\sum_{S} pd^{s} \cdot pp^{s'} \cdot OC^{ss'} + \sum_{S'}\sum_{S} pd^{s} \cdot pp^{s'} \cdot HC^{ss'} + \sum_{S'}\sum_{S} pd^{s} \cdot pp^{s'} \cdot WC^{ss'} + \sum_{S'}\sum_{S} pd^{s} \cdot pp^{s'} \cdot TO^{ss'} + \sum_{S'}\sum_{S} pd^{s} \cdot pp^{s'} \cdot CU^{ss'} \tag{3}$$

$$OC^{ss'} = \sum_{t}\sum_{b}\left(\sum_{l} OL_l \cdot e_{blt}^{ss'}\right) \tag{4}$$

$$HC^{ss'} = \sum_{t}\sum_{b}\left(HL \cdot I_{bt}^{ss'} + \sum_{h} HH \cdot I'^{ss'}_{bht}\right) \tag{5}$$

$$WC^{ss'} = \sum_{b}\sum_{t}\left(WL_b \cdot o_{bt}^{ss'} + \sum_{h} WH_b \cdot o'^{ss'}_{bht}\right) \tag{6}$$

$$TO^{ss'} = \sum_{t}\left(\sum_{j} ML_j \cdot z_{jt} + \sum_{h} LH_h \cdot u_{ht}^{ss'}\right) \tag{7}$$

$$CU^{ss'} = \sum_{b}\sum_{t}\left(CL_b \cdot n_{bt}^{ss'} + \sum_{h} CH_b \cdot nn_{bht}^{ss'}\right) \tag{8}$$

$$\sum_{j} z_{jt} \leq N \qquad \forall t \tag{9}$$

$$e_{bt}^{ss'} \leq \sum_{j}(1 - dis_z) \cdot \left(\sum_{j} AM_{rj} \cdot z_{jt}\right) + AL_r - FW_{rt} \qquad \forall b : 3(r-1) + 1 \leq b \leq (r \cdot 3), t, s, s' \tag{10}$$

$$I_{bt}^{ss'} = I_{b,t-1}^{ss'} + e_{bt}^{ss'} - \sum_{h} q_{bht}^{ss'} - o_{bt}^{ss'} + n_{bt}^{ss'} \qquad \forall b, t > 1, s, s' \tag{11}$$

$$I_{bt}^{ss'} = I0_b + e_{bt}^{ss'} - \sum_{h} q''^{ss'}_{bht} - o_{bt}^{ss'} + n_{bt}^{ss'} \qquad \forall b, t = 1, s, s' \tag{12}$$

$$I_{bt}^{ss'} \geq SS_b^{ss'} \forall b, t, s, s' \tag{13}$$

$$q_{bht}^{ss'} - I'^{ss'}_{bht} + I'^{ss'}_{bh,t-1} - o''^{ss'}_{bht} + nn_{bht}^{ss'} = D_{bht}^{s} \ \forall b, h, t > 0, s, s' \tag{14}$$

$$q_{bht}^{ss'} - I'^{ss'}_{bht} + I0'_{bh} - o''^{ss'}_{bht} + nn_{bht}^{ss'} = D_{bht}^{s} \ \forall b, h, t > 0, s, s' \tag{15}$$

$$o_{bt}^{ss'} = max\left\{0, I_{b,t-LF}^{ss'} - \sum_{h} q''^{ss'}_{bht} - o_{b,t-LF}^{ss'}\right\} \forall b, s, s', t : t \geq LF + 1 \tag{16}$$

$$o_{bt}^{ss'} = oa_{bt}^{ss'} \forall b, s, s', t : t \leq LF \tag{17}$$

$$o'^{ss'}_{bht} = max\left\{0, I'^{ss'}_{bh,t-LF} - o'^{ss'}_{b,h,t-LF}\right\} \forall b, h, s, s', t : t \geq LF + 1 \tag{18}$$

$$o'^{ss'}_{bht} = oa'^{ss'}_{bht} \forall b, l, s, s', t : t \leq LF \tag{19}$$

$$\sum_{b} I_{bt}^{ss'} \leq CapL \qquad \forall t, s, s' \tag{20}$$

$$\sum_{b} I'^{ss'}_{bht} \leq CapH_h \qquad \forall h, t, s, s' \tag{21}$$

$$\sum_{b} q_{bht}^{ss'} \leq u_{ht}^{ss'} \cdot MTC \qquad \forall h, t, s, s' \tag{22}$$

$$z_{jt}, u_{ht}^{ss'} \in \{0,1\} \qquad \forall j, h, t, s, s' \tag{23}$$

$$e_{bt}^{ss'}, q_{bht}^{ss'}, I_{bt}^{ss'}, I'^{ss'}_{bht}, o_{bt}^{ss'}, o'^{ss'}_{bht} \geq 0 \text{ and integer} \qquad \forall b, h, t, s, s' \tag{24}$$

$$Min\ z_1^R = n \cdot L + \lambda \cdot \sum_{s'} \sum_{s} pd^s \cdot pp^{s'} \cdot \xi_{ss'} \tag{25}$$

$$Min\ z_2^R = n \cdot L' + \lambda \cdot \sum_{s'} \sum_{s} pd^s \cdot pp^{s'} \cdot \xi'_{ss'} \tag{26}$$

$$Min\ z_3^R = n \cdot L'' + \lambda \cdot \sum_{s'} \sum_{s} pd^s \cdot pp^{s'} \cdot \xi''_{ss'} \tag{27}$$

$$\xi_{ss'} = n_{bt}^{ss'} + \sum_{h} nn_{bht}^{ss'} \tag{28}$$

$$\xi'_{ss'} = o_{bt}^{ss'} + \sum_{h} o'^{ss'}_{bht} \tag{29}$$

$$\xi''_{ss'} = OC^{ss'} + HC^{ss'} + WC^{ss'} + TO^{ss'} + CU^{ss'} \tag{30}$$

$$\xi_{ss'} - \xi^*_{ss'} \leq L \tag{31}$$

$$\xi'_{ss'} - \xi'^*_{ss'} \leq L' \tag{32}$$

$$\xi''_{ss'} - \xi''^*_{ss'} \leq L'' \tag{33}$$

$$z_1^{NIS} = \max\{z_1(x_2^{PIS}), z_1(x_3^{PIS})\} \tag{34}$$

$$z_2^{NIS} = \max\{z_1(x_1^{PIS}), z_1(x_3^{PIS})\} \tag{35}$$

$$z_3^{NIS} = \max\{z_1(x_1^{PIS}), z_1(x_2^{PIS})\} \tag{36}$$

$$\mu_i(x) = \begin{Bmatrix} 1 & if & z_i^R < z_i^{PIS} \\ \dfrac{z_i^{NIS} - z_i^R}{z_i^{NIS} - z_i^{PIS}} & if & z_i^{PIS} \leq z_i^R \leq z_i^{NIS}, \\ 0 & if & z_i^R > z_i^{NIS} \end{Bmatrix} \tag{37}$$

$$Max\ \tau(x) = \gamma \cdot \tau_0 + (1 - \gamma) \cdot \sum_{i} \theta_i \cdot \mu_i(x) \tag{38}$$

$$\tau_0 \leq \mu_i(x)\ i = 1,2,3 \tag{39}$$

$$x \in Q(x) \tag{40}$$

$$\tau_0 \in [0,1] \tag{41}$$