

Integrated Product Blending Optimization for Oil Refinery Operations

Amit Purohit*, Tukaram Suryawanshi**

* ABB, GISL Bangalore, 560048 India
(Tel: +91-80-67579950; e-mail: amit.purohit@in.abb.com).

** Infosys, Mysore, 570027 India (e-mail:
tukaram.suryawanshi@infosys.com)

Abstract: Refinery is a multiproduct manufacturing plant. Crude oil is processed to get intermediate products which are blended to meet quantity, quality and schedule specification of the final products. Refinery optimization is a complex problem therefore it is broken down into sub-problems which are solved independently. The solution obtained using this approach can be improved by integrating different sub-problems for real-time optimization. Refinery works on very small Gross Refinery Margin (GRM); off specification product blends results in considerable cost overhead because product blending is the last operation in the refinery process. Therefore we propose a method for real time integration of product blending with secondary process units to significantly improve the GRM. This method is designed and implemented in the present work. A case study is included to demonstrate the benefits of the proposed method.

Keywords: Blending, Nonlinear programming, Optimization, Refinery operations.

1. INTRODUCTION

Refinery is a multiproduct manufacturing plant. A typical refinery operates as a continuous process producing many products such as gasoline, aviation fuel, diesel etc. Different intermediate products are blended to get final refinery products with desired quantity, quality and schedule specifications. Therefore planning, scheduling and optimization are of significant importance to ensure availability of right products at required time, quantity and quality. Refineries operate with high volume and razor thin Gross Refinery Margin (GRM). Hence, even small improvement in GRM has significant impact on the refinery profit.

Zhang and Zhu (2000) propose site level and process level decomposition scheme for the refinery optimization problem. Jia and Ierapetritou (2003) propose spatial decomposition of the refinery wide optimization, because the original optimization problem is mathematically intractable. They combine the primary and secondary process units and categorize them as production units. In general, the nature of operations in the primary and secondary units is different. As a result, we propose to categorize them as two separate production units, as discussed in section 2. Figure 1 shows the spatial decomposition of the refinery optimization problem (Mendez et al., 2006).

Typically, refinery optimization problem is broken down into sub-problems using spatial decomposition scheme proposed by Jia and Ierapetritou (2003). These sub-problems are solved as independent optimization problems and the combined results are considered as approximate solution to the overall refinery optimization problem. There are several commercial tools available for solving standalone refinery optimization

problems. Aspen BlendTM and Aspen PIMS-MBOTM from AspenTech are software products for online and offline blending optimization problems. EBCTM, OpenBPCTM and BlendTM, are Honeywell products for online and offline blending optimization. Profit ControllerTM from Honeywell and ROMeoTM from Invensys are online optimization solutions for primary and secondary process units.

Refinery optimization literature shows that researchers have looked at three broad directions: 1. Improving process models of the non-linear blending and other refinery processes. 2. Modeling the uncertainty in the refinery blending process using stochastic programming framework. 3. Different possibilities of integrating Model Predictive Control (MPC), product blending optimization and scheduling problems. Subsequent three paragraphs summarize the research work.

Singh (1997) provides an overview of the blending optimization problem. Shokri et al. (2009) provide the description of the real time optimization applications to refineries. Kelly (2004) proposes a generic model framework for the refinery wide planning optimization problems. It gives a good insight into the nature of non-linear modeling needed for the refinery optimization. Cheng (2011) proposes Kalman Filter to estimate blend component properties based on the product measurements.

Monder (2001) and Zhang et al. (2002) are early work on incorporating uncertainty in blending optimization. Wang et al. (2007) propose chance constraint formulation to address parameter uncertainty in the online blending optimization. They propose an intelligent hybrid algorithm using Neural Network and Genetic algorithm. This method has to overcome practical challenge of balancing execution time and solution accuracy for successful industrial acceptance.

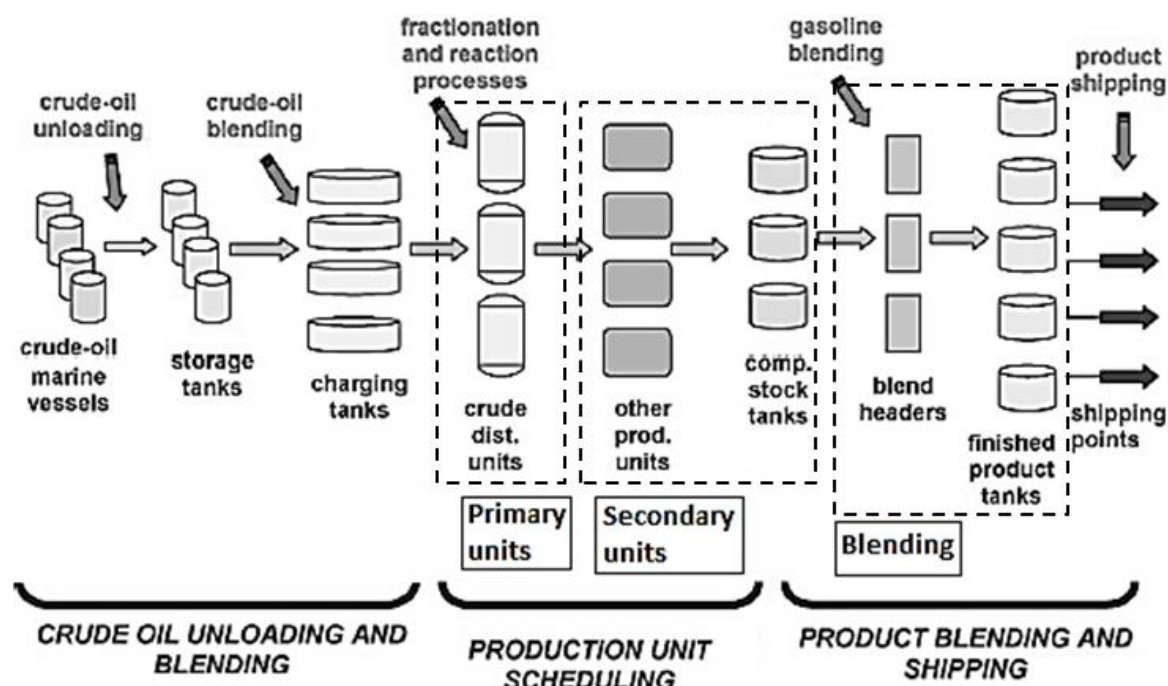


Fig. 1. Schematic division of refinery wide optimization

Mendez et al. (2006) propose a method for integrating product blending optimization and short term scheduling. Their formulation can handle non-linear product properties and variable recipes. Kelly and Mann (2003a, b) propose a scheduling formulation for crude blending. They show that proposed solution can bring multi-billion dollar benefits to the refinery. Zanin et al. (2002) propose to integrate the secondary unit, FCC, optimization to the linear MPC problem. They call this strategy as optimizing controller which is also referred to as economic MPC or profit controller in process control literature.

Existing optimization approach can be improved by integrating different refinery optimization sub-problems in Real Time Optimization (RTO). In this work we propose to integrate product blending and secondary unit optimization sub-problems; product blending is the last operation in the refinery process therefore integration with secondary units will result in improved optimization of final product blends. In general, the proposed integrated optimization will improve the Gross Refinery Margin (GRM).

The rest of this paper is organized as follows: Section 2 presents the proposed optimization approach; section 3 presents the mathematical formulation; section 4 contains a case study to demonstrate the benefits of the proposed approach over existing approach. Section 5 presents the conclusions; Appendix A describes blend laws.

2. PROPOSED OPTIMIZATION APPROACH

Spatial decomposition of refinery optimization transforms the originally intractable problem into a set of tractable sub-problems; but this tractability comes at the cost of optimality. Sub-problems are solved independent of each other therefore,

their solutions are independently optimal but collectively inferior. Hence, there is a good opportunity to improve the GRM by solving sub-problems in an integrated fashion. Figure 2 schematically shows the proposed integration. Traditionally, scheduling problem is solved to get the optimal blend recipe of the specified intermediate components. These specifications are issued as targets to the primary and secondary process unit RTO and product blending RTO. Independent optimization problems are solved to get best operating point for secondary unit and blending operation. This hierarchical formulation decouples product blending from the rest of the refinery which results in localized optimization in product blending section of the refinery. Final products are not of exact specification as predicted by the optimal schedule because of multiple reasons such as simplified process models used in scheduling, incorrect tank inventory data, unscheduled maintenance etc. Therefore, it is evident that the final outcome of the independent optimization problems do not give overall optimal solution.

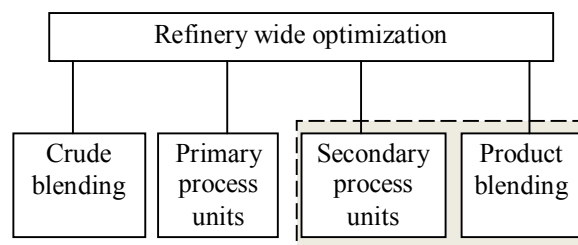


Fig. 2. Schematic of partial integration between secondary unit and product blending

We propose to partially integrate the product blending and secondary unit optimization problems. Proposed integration

approach intends to preserve the original structure of both the problems. Therefore, the proposed method can be applied to existing plants with multiple blenders, multiple secondary process units and legacy optimization solutions.

This optimization approach was not attempted so far because of multiple reasons such as lack of control over rundown streams, unavailability of premixing infrastructure to fine-tune feed properties etc. Refineries in India have shown willingness to make configuration changes to enable integrated blending and secondary unit optimization because of its potential to improve GRM.

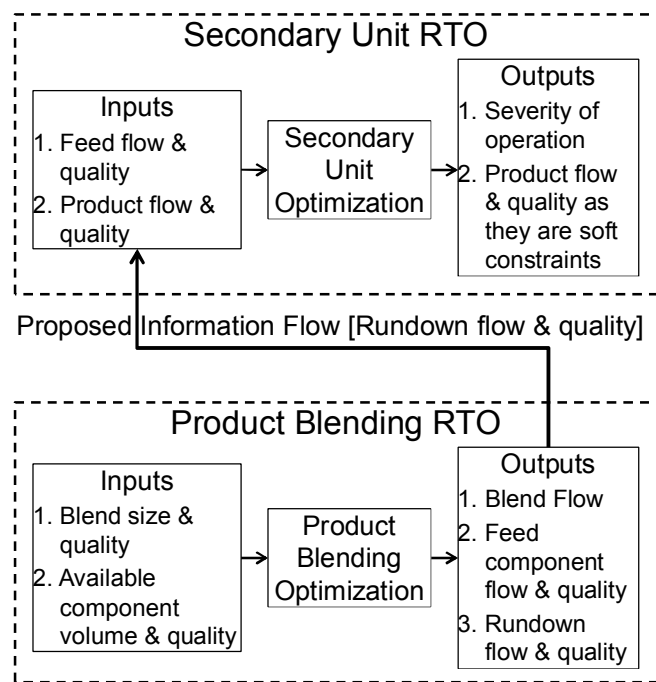


Fig. 3. Schematic of proposed integrated secondary unit and blend optimization formulation

Proposed method includes the secondary unit output, rundown flow and quality, and feed component quality as the decision variables in the blending problem; see Figure 3. This approach introduces additional source of nonlinearity in the form of bilinear terms. Proposed method handles nonlinear blend laws, additional nonlinearity and real time solution requirement. In this formulation, blending optimization demands secondary process unit to provide certain quality and flow to achieve better optimization results such as on-specification blend which was otherwise off-specification and lower quality give away. This approach partially integrates the two refinery sub-problems. Next step is to make process unit communicate to the blender if it cannot supply or partially supply the demanded quality or quantity. This step would complete the integration of two units. This part will be addressed in our future work.

3. MATHEMATICAL FORMULATION

3.1 Problem Formulation

Problem formulation includes multiple blenders and storage

tanks as shown in blending section of Figure 1. Properties of the final products are modeled using blend laws which relate final product property to quantities and properties of feed components. Blend product properties are either linearly or non-linearly blended on the basis of volume or mass of the feed components. For instance Research Octane Number (RON) of the blend is modeled by linear blend law while Reid Vapor Pressure (RVP) of the blend is modeled by non-linear blend law. Brief description of blend laws is included in Appendix A. Following nomenclature is used in the mathematical formulation presented in this section:

Indices

b	blenders
i	intermediate components
j	properties or qualities
k	rundown streams

Parameters and variables

PE_j	estimate of property j
W_j	property variable j
P_Cost_j	cost of property j
OR_j	off-spec ratio for property j
F_i	feed flow rate of component i
BV_{ij}	property j of feed component i
C_Cost_i	cost of component i
P_Lim_j	property j limit at which giveaway is minimized
FS_k	segregation flow for rundown k
TF_b	total flow of blender b
$*_Tgt$	target value of variable
$F(x)$	nonlinear objective function
f	nonlinear constraint function
\hat{f}	linearized form of nonlinear constraint function f
x	variables in nonlinear objective/ constraint function
λ	vector of estimated Lagrangian multipliers
ρ	penalty parameter
$A2$	coefficients of nonlinear variables x in linear constraint
$b1, b2$	equality to the constraints
l, u	lower and upper bounds on constraints

Blend optimization is subject to different types of constraints. These constraints are operational constraints (equipment limits on component flow), inventory constraints (volume limits on feed components) and quality constraints (analyzer limits, and tank property specification). Following are the constraints for blending optimization:

Average property constraint: When blending into a destination tank, the product property in tank cannot violate the product specifications. These limits are transformed as average property constraints.

Instantaneous property constraint: When analyzer is used to detect product property at blend header, analyzer has limits imposed on its measurements. Property detected by analyzer

should not cross the specified analyzer limits. These analyzer limits are considered as instantaneous property constraints.

Average composition constraint: It is a constraint on concentration of each component in destination tank when destination tank property integration is nonlinear.

Equipment constraint: It is a constraint on component flows based on hydraulic constraints of the equipment.

Cost constraint: It is a constraint on the cost function value. In case of 'Minimum Giveaway' optimization mode the value of cost function should not exceed 'minimum cost calculated in 'Cost' mode solved earlier.

Material balance constraint: It is an overall material balance constraint for each blender used in blending operation.

Component balance constraint: It is component balance constraint for each feed component used in the blending operation.

Rundown constraint: It is a material balance constraint on rundown stream used in the blending problem.

Blend Volume constraint: It is a constraint on total blend quantity specification for the blending operation.

Component volume availability constraint: It is a constraint on the component volume available for blending operation.

Following are decision variables for blending optimization:

- (i) Feed component volume fraction (R_i)
- (ii) Feed component volumetric flow (F_i)
- (iii) Product property variable (W_j)
- (iv) Total flow to blender (TF_b)
- (v) Segregation flow - flow from rundown stream to segregation tank (FS_k)
- (vi) Blend volume - predicted volume in destination tank over which the product is expected to be on-specification
- (vii) Feed component property ($BV_{i,j}$)
- (viii) Rundown total flow (FR_k)

Blending optimization problem is formulated as multi-objective optimization. Its primary objective is to control the blending process so that the products are on-specification. Once products are on-specification, the secondary objective is to minimize cost or giveaway or distance of decision variable from target value (minimum distance). Following combination of objectives can be used -

1. Control-Cost
2. Control-Giveaway
3. Control-Minimum Distance
4. Control-Cost-Giveaway

1. Control objective:

Objective of control mode is to maintain product property in specified range (make it on-specification). Objective function when blending into destination tank is given as

$$Min F = \sum_b \left(\sum_j (PE_j - W_j)^2 P_Cost_j OR_j \right) \quad (1)$$

Decision variables – all variables mentioned in section 3.1.

Constraints – all constraints mentioned in section 3.1 except cost constraint.

2. Cost Objective:

Objective of this mode is to minimize the cost of feed components. Objective function is given as

$$Min F = \sum_b \left(\sum_i C_Cost_i F_i \right) \quad (2)$$

3. Giveaway objective:

Objective of this mode is to minimize quality giveaway. In refinery terms giveaway is giving away a product of better quality than specifications. Minimizing the giveaway is necessary to reduce the money lost because of giving product of better quality than required by product specifications. Objective function is given as

$$Min F = \sum_b \left(\sum_j (PE_j - P_Lim_j)^2 P_Cost_j \right) \quad (3)$$

4. Minimum distance objective:

Objective of this mode is to minimize distance between current value of variable and its target value. Objective function for rundown flow is given as

$$Min F = \sum_b \left(\sum_k (FS_k - FS_Tgt_k)^2 Rundown_Cost_k \right) \quad (4)$$

Decision variables for all objectives except control objective are all variables mentioned in section 3.1 except total flow and product property variables. Constraints for objectives other than control objective are all constraints mentioned in section 3.1.

3.2 Problem Solution

One of the main solution requirements is to solve the proposed problem in real time. If that is not possible then the intermediate iteration result after fixed time interval should be feasible and better than the previous iteration results. This requirement ensures that a feasible solution better than the initial guess is provided for cases where solver cannot converge in available time for real time optimization. Proposed problem is solved using MINOS solver because it is a feasible region search based robust NLP solver (Chen et al., 1996) and meets all the solution requirements.

The objective function is formulated as Augmented Lagrangian form by introducing Lagrangian multipliers and penalty parameters. Sequence of iterations is performed, each

one requiring solution of linearly constrained sub-problems. These sub-problems contain the original linear constraints and bounds on variables as well as linearized form of nonlinear constraints.

$$\min_x F(x) - \lambda_k^T (f - \bar{f}) + \frac{1}{2} \rho (f - \bar{f})^T (f - \bar{f})$$

Subject,

$$\begin{aligned} \bar{f} &= b_1 \\ A_2 x &= b_2 \\ l &\leq (x) \leq u \end{aligned} \quad (5)$$

The values of *Lagrangian Multipliers* are calculated by solver. Penalty parameters are specified to the solver. Reduced-gradient algorithm is used to minimize objective function.

4. CASE STUDY

A gasoline blending case study with real component property and blend specification data is presented here. This case study demonstrates advantages of the proposed optimization approach over traditional blending optimization. In theory as many as 20 components can be blended to get gasoline but typically 4-5 components are blended in practice. Two component gasoline blending is presented in this case study which is realistic and clearly highlights the benefits of proposed optimization approach. Proposed method has been extensively tested for multiple components and multiple blenders but those results are not of interest here.

Figure 4 depicts the schematic of blending process considered for the case study. Iso-Paraffin and Naphtha are blended to get the gasoline. Naphtha is fed from the intermediate product tank while Iso-Paraffin is fed from the upstream Isomerization [ISOM] unit.

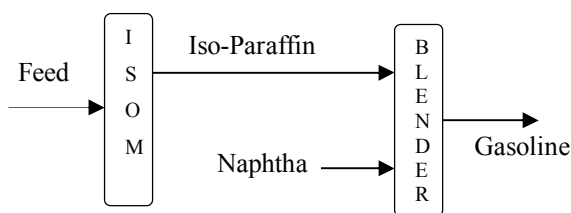


Fig. 4. Schematic of Gasoline blending

Table 1, provide the component quality specification for Iso-Paraffin and Naphtha components used in blending operation.

Table 1. Component Property Data

Properties	Iso-Paraffin (feed1)	Naphtha (feed2)
RON	92	85
MON	90	77

Table 2, provide the product quality and quantity specification for the gasoline.

Table 2. Gasoline product specification

Gasoline Blend Specification		
Properties	Low	High
RON	92	95
MON	83	87
Flow	400	400

Scheduling layer provides blend recipe to the blending optimization layer. Blending optimization then solves for component flows to meet the product quality and quantity specification. Traditional blend optimization with control-cost objectives results in solution wherein the product is off-specification as shown in Table 3. Resulting product blend would either require re-blending before shipping it out of refinery or delaying the blend which then have to be shipped at higher cost and demurrage expense. Either of these interventions decreases GRM by increasing the final product cost by additional re-blending cost, inventory cost, demurrage and opportunity cost of refinery assets.

Table 3. Traditional blend optimization result (product properties and feed flow rates)

Properti es/ Flow	Iso-Paraffin (feed1)	Naphtha (feed2)	Gasoline product	Result
RON	92	85	89.2	Off-Spec
MON	90	77	84.8	On-Spec
Flow	240*	160	400	

(*) – The flow limit for component is reached but blend is off-specification (Off-Spec).

Same problem is solved with the proposed method to demonstrate the benefits over traditional method. Proposed blend optimization also receives blend recipes from the scheduling layer similar to traditional blending optimization. But unlike traditional blending optimization, proposed method has integration with the upstream secondary process unit. Proposed optimization formulation with control-cost objectives results in a solution such that the gasoline product blend is on-specification as shown in Table 4. Proposed blend method issues a new RON set point to upstream unit from which feed1 is fed. The upstream unit is then optimized to satisfy the new value of RON by changing its operating point.

Table 4. Proposed blend optimization result (product properties, feed properties and flow rates)

Properti es / Flow	Iso-Paraffin (feed1)	Naphtha (feed2)	Gasoline product	Result
RON	97	85	92.2	On-Spec*
MON	90	77	84.8	On-Spec
Flow	240	160	400	

(*) – RON is on specification (On-Spec); it was Off-Spec in the traditional formulation

It is evident from the case study that the proposed formulation avoided off-specification product blend by proposing new value of RON for feed1 and hence improved GRM by saving re-blending cost, demurrages and valuable time of the refinery assets. Therefore proposed blending formulation has multiple benefits which finally result in operational advantages.

5. CONCLUSION

Blend optimization formulation that is proposed in this paper partially integrates product blending optimization with upstream secondary process units. The proposed optimization approach improves GRM by saving additional re-blending and demurrage costs through better real time optimization. Proposed integration is possible because refiners have shown interest in making configuration changes for deploying proposed optimization approach. Proposed optimization approach is designed to replace existing optimization solution with minimal effort. The case study presented in this paper demonstrates that the proposed integrated approach results in multi fold benefits to the refinery. These benefits translate into improved GRM and hence provide cost advantage in the marketplace.

ACKNOWLEDGEMENTS

Special thanks to Niket Kaisare and Vinay Kariwala from ABB Corporate Research for providing their comments on the draft of the paper.

REFERENCES

- Adetola V., & Guay M. (2010). Integration of real-time optimization and model predictive control. *Journal of Process Control*. 20, 125–133.
- Chen X., Rao K.S., Yu J., & Pike R.W. (1996). Comparison of GAMS, AMPL, and MINOS for optimization. *Chemical Engineering Education*. 220-227.
- Cheng H. (2011). Real time optimization of the gasoline blending process with unscented kalman filter. *International Conference on Internet Computing & Information Services*. 148-151.
- Honeywell Inc. (2008). OpenBPC (Open Blend Property Control). *Configuration Guide Release 3.2.0*. Phoenix, Arizona.
- Jia Z., & Ierapetritou M. (2003). Mixed-integer linear programming model for gasoline blending and distribution scheduling. *Ind. Eng. Chem. Res.* 42, 825-835.
- Kelly, J.D. (2004). Formulating production planning models. *Chemical Engineering Progress*. 43–50.
- Kelly, J.D., & Mann, J.L. (2003a) Crude-oil blend scheduling optimization: An application with multi-million dollar benefits: Part I. *Hydrocarbon Processing*. 47–53.
- Kelly, J.D., & Mann, J.L. (2003b). Crude-oil blend scheduling optimization: An application with multi-million dollar benefits: Part II. *Hydrocarbon Processing*. 72–79.
- Mendez C.A., Grossmann I.E., Harjunkoski I., & Kabor P. (2006). A simultaneous optimization approach for off-line blending and scheduling of oil-refinery operations. *Computers and Chemical Engineering*. 30, 614–634.
- Monder D.S. (2001). Real-time optimization of gasoline blending with uncertain parameters, *MS Thesis*. University of Alberta, Canada.
- Singh A. (1997) Modeling and model updating in real-time optimization of gasoline blending, *MS Thesis*. University of Toronto, Canada.
- Shokri S., Hayati R., Marvast M.A., Ayazi, M., & Ganji H. (2009). Real time optimization as a tool for increasing petroleum refineries profits. *Petroleum & Coal*. 2009, 51 (2) 110-114.
- Wang W., Li Z., Zhang Q., & Li Y. (2007). On-line optimization model design of gasoline blending system under parametric uncertainty. *Proceedings of the 15th Mediterranean Conference on Control & Automation, Athens – Greece*. T24-007.
- Zanin, A.C., Gouvêa T. D., & M., Odloak, D. (2002). Integrating Real-Time Optimization into The Model Predictive Controller Of The Fcc System. *Control Engineering Practice*. 10 (8), 819-831.
- Zhang, N., & Zhu, X.X. (2000). A novel modelling and decomposition strategy for overall refinery optimization. *Computers and Chemical Engineering*. 24, 1543.
- Zhang, Y., Monder, D., & Forbes, J.F. (2002). Real-time optimization under parametric uncertainty: a probability constrained approach. *Journal of Process control*. 373-389.

APPENDIX A. BLEND LAWS

Blend law used to estimate product property based on volume/mass fractions or volume/mass flow and property of feed components are as follows:

1. Linearly blended by component fractions in tanks:
The property of product blend is linear function of component volume/mass fractions and properties

$$PE_j = \sum_i X_i BV_{i,j}$$

Where, X_i is volume/mass fraction of component i in the product tank.

2. Linearly blended by component flows in blend headers:
The instantaneous property of product blend is linear function of component volume/mass flow rates and properties

$$PE_j = \frac{\sum_i F_i BV_{i,j}}{\sum_i F_i}$$

Where F_i is volume/mass flow rate of component i to the blend header.