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Selection of bottleneck detection methods using multi-criteria decision making

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Study Overview

Identifying **production bottlenecks** is essential for improving manufacturing throughput

One of the first steps in identifying the production bottleneck is selecting the most suitable bottleneck detection method (BDM)

However, **choosing the right BDM** for different assembly line scenarios is a complex task.

This study applies the Technique for Order Preference by Similarity to Ideal Solution (**TOPSIS**), a Multi-Criteria Decision-Making (MCDM) method, to **rank and select the most suitable BDM** for 3 distinct production lines.

Unlike past research focused on general industrial decisions, this work introduces a **tailored approach** for BDM selection in **distinct manufacturing environments**.

Azhar et al., 2021; Basílio et al., 2022

Bottleneck

It's the resource that limits the throughput of a process

Manufacturing System

Static: Bottlenecks are typically fixed, no variation or special causes affect the process

Dynamic: Bottlenecks can shift due to variability in process times or unforeseen disruptions

Shifting Bottleneck

Bottleneck Analysis

Short-term: Temporary (e.g., machine breakdown)

Useful in identifying special causes and allowing for a quick reaction

Long-term: Persistent constraints over extended periods (e.g., relatively high process time)

Provides value in planning and designing a manufacturing system

Roser et al., 2004; Kuo et al., 1996; Betterton & Silver, 2012

Bottleneck Detection Methods

Category	Pros	Cons
BDMs based on Static Models	**More practical** for environments with **limited digital data** and lower technological investment	Lack of short-term analysis and **precision**
BDMs based on Simulations	**More accurate** than static models, capable of both short-term and long-term analysis	Requires **significant setup time** and may overlook process nuances
BDMs based on Data-Driven Approaches	**High accuracy** and efficiency, capable of both short-term and long-term analysis	Requires **real-time data**, which may not always be available

Xu et al., 2021; Tang et al., 2024; Betterton & Silver, 2012; Subramaniyan et al., 2016; Lai et al., 2021; Roser et al., 2017; Chiang et al., 2000; Roser et al., 2015; Roser & Nakano, 2015

Bottleneck Detection Methods

Category	BDM	Description
BDMs based on Static Models	Process Time Method (PTM)	Identifies bottlenecks by comparing resources' average process times
	Utilization Method (UM)	Detects bottlenecks based on the utilization rate of each resource
BDMs based on Simulations	Simulation Methods (SM)	Simulates system behavior to observe where bottlenecks emerge
BDMs based on Data-Driven Approaches	Turning Point Method (TPM)	Finds bottlenecks by analyzing shifts in station throughput over time
	Interdeparture Time Variance Method (ITVM)	Locates bottlenecks by measuring variance in part interdeparture times
	Active Period Method (APM)	Detects bottlenecks by tracking the active working periods of stations
	Bottleneck Walk Method (BWM)	Observes inventory build-up between stations to spot bottlenecks
	Arrow Method (AM)	Uses directional inventory flow to infer likely bottleneck locations
	Inventory-Based Methods (IBM)	Identifies bottlenecks by monitoring inventory levels and accumulation

Xu et al., 2021; Tang et al., 2024; Betterton & Silver, 2012; Subramaniyan et al., 2016; Lai et al., 2021; Roser et al., 2017; Chiang et al., 2000; Roser et al., 2015; Roser & Nakano, 2015

TOPSIS for BDM Selection

Developed by Hwang & Yoon, in 1981

Identifies an ideal and anti-ideal solution, ranking alternatives based on their proximity to both

Why TOPSIS?

Straightforward Results
Best solution is the one closest to the ideal and furthest from the anti-ideal

Ease of Use
No complex computations, spreadsheet-friendly

Minimal input requirements
Compared to other MCDM methods

TOPSIS 5-Step Method

01 **Define Performance Scores**
Define the performance for each alternative based on multiple criteria

02 **Weight Criteria**
Assign importance to each criterion

03 **Normalize Data**
Adjust values to ensure comparability

04 **Calculate Distances**
Measure the distance of each alternative from the ideal and worst-case scenarios

05 **Rank Alternatives**
Rank based on proximity to the ideal solution relative to the worst-case

Tzeng & Huang, 2011; Ishizaka & Nemery, 2013; Madanchian & Taherdoost, 2023

Alternatives and Criteria

Alternative
PTM
UM
TPM
ITVM
APM
BWM
AM
IBM
SM

A 1–3 scale was used for performance scores, as the classification was mostly based on document analysis and qualitative inputs rather than quantitative data

	Rating		
Criterion	**1**	**3**	**Objective**
Data Availability	Manual data collection	Requires digital manufacturing data	↓
Accuracy	Low accuracy	High accuracy	↑
Adaptability	Not flexible	Easily adaptable to different line dynamics	↑
Time Requirement	Quick to apply	Requires more time to be applied	↓

Performance Scores

Performance scores on the *m* selected criteria *i* were attributed to each *a* of the *n* BDMs (alternatives):

	Criterion			
Alternative	**Data Availability**	**Accuracy**	**Adaptability**	**Time Requirement**
PTM	1	1	3	2
UM	2	1	3	1
TPM	3	2	2	2
ITVM	2	3	3	2
APM	3	3	1	2
BWM	1	3	1	3
AM	3	2	2	2
IBM	3	1	1	2
SM	2	2	2	3

Data Availability:
1: PTM and BWM, requiring only manual data collection ;
2: UM, ITVM, and SM require basic real-time data (e.g., UM only needs utilization rates; ITVM mainly needs final timestamps);
3: TPM, APM, AM, and IBM demand detailed, interdependente real-time data, such as start and end times of each process or buffer states.

Accuracy:
Scored based on results from previous studies:
1: PTM, UM, and IBM;
2: TPM and AM;
3: BWM, APM, and ITVM

Adaptability:
1: APM, BWM, and IBM struggle in non-standard layouts (e.g., lack of buffers between stations or having multi-operator dynamics);
2: TPM, AM, and SM can be adapted with some adjustments;
3: ITVM, PTM, and UM are easily adjustable to unusual process dynamics.

Time Requirement:
1: UM, due to simple calculations of utilization rates;
2: Other data-driven methods and the PTM (depending on the sample size needed);
3: BWM (extensive observations needed) and SM (model building and calibration).

Roser & Nakano, 2015; Roser et al., 2017; West et al., 2022; Roser et al., 2015; Roh et al., 2018; Betterton & Silver, 2012

Performance Scores

The table's values are the values of the decision matrix $X = (x_{ai})$ where ***i*** **= 1, …,** ***m*** **criteria** and ***a*** **= 1, …,** ***n*** **alternatives**.

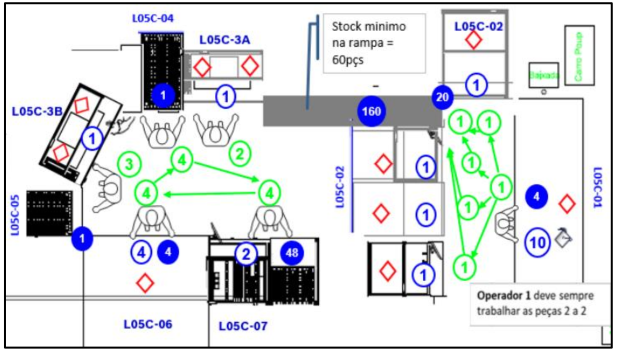
Alternative	Criterion			
	Data Availability	Accuracy	Adaptability	Time Requirement
PTM	1	1	3	2
UM	2	1	3	1
TPM	3	2	2	2
ITVM	2	3	3	2
APM	3	3	1	2
BWM	1	3	1	3
AM	3	2	2	2
IBM	3	1	1	2
SM	2	2	2	3

$$X = \begin{bmatrix} 1 & 1 & 3 & 2 \\ 2 & 1 & 3 & 1 \\ 3 & 2 & 2 & 2 \\ 2 & 3 & 3 & 2 \\ 3 & 3 & 1 & 2 \\ 1 & 3 & 1 & 3 \\ 3 & 2 & 2 & 2 \\ 3 & 1 & 1 & 2 \\ 2 & 2 & 2 & 3 \end{bmatrix}$$

Roser & Nakano, 2015; Roser et al., 2017; West et al., 2022; Roser et al., 2015; Roh et al., 2018; Betterton & Silver, 2012

Production Line Profiles and Limitations

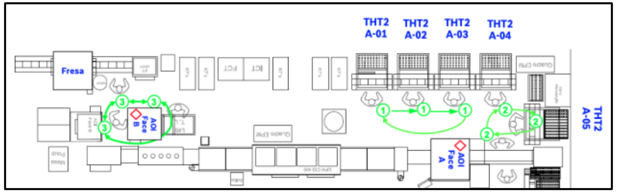
L05C



No real-time data available; highly limited data environment

Simple dynamics, **similar to classical flow lines**

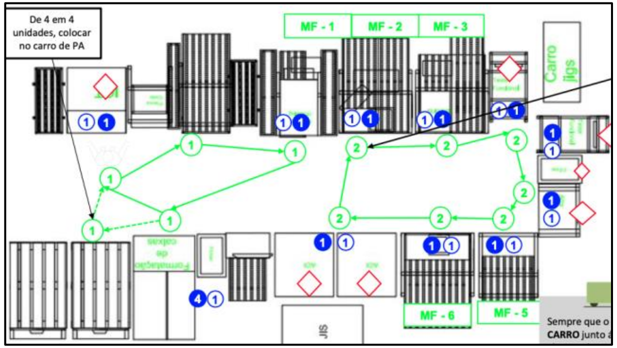
THT2A



No real-time data, but **structured buffer systems** support operations

Stable and **regular flow line** behavior

L35



Some **real-time data available**, but inconsistent

Irregular flow, requiring flexible and adaptive methods

Criteria Weight

Since the lines have distinct characteristics, the criteria weights were adapted for each case using a **Direct Rating Method**.

This method works by assigning weights directly to each criterion for each line **based on the decision-maker's experience and understanding**

Although it relies on subjective judgement, it is a quite **simple, fast, and intuitive** method to use.

	Criterion			
Line	Data Availability	Accuracy	Adaptability	Time Requirement
L05C	0,5	0,2	0,2	0,1
THT2A	0,5	0,3	0,1	0,1
L35	0,2	0,3	0,4	0,1

Across all lines, **time requirement** is the least important, serving mainly as a tiebreaker.

For **L05C**, **data availability** is prioritized due to the lack of real-time data. **Accuracy** and **adaptability** are moderately weighted, as the line resembles a typical flow line.

For **THT2A**, **data availability** remains crucial, while **accuracy** gains importance over **adaptability**, given its a flow line setup.

For **L35**, with some real-time data, **adaptability** is prioritized to handle its unusual flow dynamics. **Accuracy** is also important, while **data availability** becomes less critical.

Data Normalization

- Even though all scores are on a 1–3 scale, some criteria are to be **maximized** and others **minimized**, so normalization is needed.

- The normalization is done by **dividing each performance by the highest value, u_a^+**, if the criterion is to be **maximized**:

$$r_{ai} = \frac{x_{ai}}{u_a^+}$$,for *a* = 1, ..., *n* and *i* = 1, ..., *m*, where $u_a^+ = max(x_{ai})$

- **Or by the lowest value, u_a^-**, if the criterion is to be **minimized**:

$$r_{ai} = \frac{x_{ai}}{u_a^-}$$,for *a* = 1, ..., *n* and *i* = 1, ..., *m*, where $u_a^- = min(x_{ai})$

- The normalized performance score matrix, r_{ai}, is as follows:

$$r_{ai} = \begin{bmatrix} 1,00 & 0,33 & 1,00 & 2,00 \\ 2,00 & 0,33 & 1,00 & 1,00 \\ 3,00 & 0,67 & 0,67 & 2,00 \\ 2,00 & 1,00 & 1,00 & 2,00 \\ 3,00 & 1,00 & 0,33 & 2,00 \\ 1,00 & 1,00 & 0,33 & 3,00 \\ 3,00 & 0,67 & 0,67 & 2,00 \\ 3,00 & 0,33 & 0,33 & 2,00 \\ 2,00 & 0,67 & 0,67 & 3,00 \end{bmatrix}$$

Distances Calculation

- The next step is to consider the criteria weights, **by multiplying the normalized matrix r_{ai} by their corresponding weights w_i**, for each assembly line distinctively:

$$v_{ai} = w_i \times r_{ai} \qquad \text{,for } a = 1, \ldots, n \text{ and } i = 1, \ldots, m$$

- For each line, the v_{ai} matrices are presented below:

$$v_{ai,L05C} = \begin{bmatrix} 0{,}50 & 0{,}07 & 0{,}20 & 0{,}20 \\ 1{,}00 & 0{,}07 & 0{,}20 & 0{,}10 \\ 1{,}50 & 0{,}13 & 0{,}13 & 0{,}20 \\ 1{,}00 & 0{,}20 & 0{,}20 & 0{,}20 \\ 1{,}50 & 0{,}20 & 0{,}07 & 0{,}20 \\ 0{,}50 & 0{,}20 & 0{,}07 & 0{,}30 \\ 1{,}50 & 0{,}13 & 0{,}13 & 0{,}20 \\ 1{,}50 & 0{,}07 & 0{,}07 & 0{,}20 \\ 1{,}00 & 0{,}13 & 0{,}13 & 0{,}30 \end{bmatrix} \quad v_{ai,THT2A} = \begin{bmatrix} 0{,}50 & 0{,}10 & 0{,}10 & 0{,}20 \\ 1{,}00 & 0{,}10 & 0{,}10 & 0{,}10 \\ 1{,}50 & 0{,}20 & 0{,}07 & 0{,}20 \\ 1{,}00 & 0{,}30 & 0{,}10 & 0{,}20 \\ 1{,}50 & 0{,}30 & 0{,}03 & 0{,}20 \\ 0{,}50 & 0{,}30 & 0{,}03 & 0{,}30 \\ 1{,}50 & 0{,}20 & 0{,}07 & 0{,}20 \\ 1{,}50 & 0{,}10 & 0{,}03 & 0{,}20 \\ 1{,}00 & 0{,}20 & 0{,}07 & 0{,}30 \end{bmatrix} \quad v_{ai,L35} = \begin{bmatrix} 0{,}20 & 0{,}10 & 0{,}40 & 0{,}20 \\ 0{,}40 & 0{,}10 & 0{,}40 & 0{,}10 \\ 0{,}60 & 0{,}20 & 0{,}27 & 0{,}20 \\ 0{,}40 & 0{,}30 & 0{,}40 & 0{,}20 \\ 0{,}60 & 0{,}30 & 0{,}13 & 0{,}20 \\ 0{,}20 & 0{,}30 & 0{,}13 & 0{,}30 \\ 0{,}60 & 0{,}20 & 0{,}27 & 0{,}20 \\ 0{,}60 & 0{,}10 & 0{,}13 & 0{,}20 \\ 0{,}40 & 0{,}20 & 0{,}27 & 0{,}30 \end{bmatrix}$$

Distances Calculation

- For each line, the $\boldsymbol{v_{ai}}$ matrices are then used to compare each alternative to an ideal and anti-ideal solution, which are defined by **collecting the best and worst performance on each criterion** of the weighted normalized decision matrices, respectively $\boldsymbol{A^+}$ **and** $\boldsymbol{A^-}$.

$\boldsymbol{A^+} = \{\boldsymbol{v_1^+}; \ldots; \boldsymbol{v_m^+}\}$,for a = 1, ..., n and i = 1, ..., m, where $v_i^+ = max_a(v_{ai})$ if the criterion is to be maximized or $v_i^+ = min_a(v_{ai})$ if the criterion is to be minimized

$\boldsymbol{A^-} = \{\boldsymbol{v_1^-}; \ldots; \boldsymbol{v_m^-}\}$,for a = 1, ..., n and i = 1, ..., m, where $v_i^- = min_a(v_{ai})$ if the criterion is to be maximized or $v_i^- = max_a(v_{ai})$ if the criterion is to be minimized

- So, for each assembly line the ideal and anti-ideal solutions are:

Ideal Solutions

$$A^+_{L05C} = \{0{,}50;\ 0{,}20;\ 0{,}20;\ 0{,}10\}$$

$$A^+_{THT2A} = \{0{,}50;\ 0{,}30;\ 0{,}10;\ 0{,}10\}$$

$$A^+_{L35} = \{0{,}20;\ 0{,}30;\ 0{,}40;\ 0{,}10\}$$

Anti-Ideal Solutions

$$A^-_{L05C} = \{1{,}50;\ 0{,}07;\ 0{,}07;\ 0{,}30\}$$

$$A^-_{THT2A} = \{1{,}50;\ 0{,}10;\ 0{,}03;\ 0{,}30\}$$

$$A^-_{L35} = \{0{,}60;\ 0{,}10;\ 0{,}13;\ 0{,}30\}$$

Distances Calculation

- The fourth step is to calculate the distance of each alternative to the ideal and anti-ideal solutions, given by $\boldsymbol{d_a^+}$ and $\boldsymbol{d_a^-}$, respectively:

$$\boldsymbol{d_a^+} = \sqrt{\sum_i (\boldsymbol{v_i^+} - \boldsymbol{v_{ai}})^2} \quad \text{,for } a = 1, \ldots, n \text{ and } i = 1, \ldots, m$$

$$\boldsymbol{d_a^-} = \sqrt{\sum_i (\boldsymbol{v_i^-} - \boldsymbol{v_{ai}})^2} \quad \text{,for } a = 1, \ldots, n \text{ and } i = 1, \ldots, m$$

- For each assembly line, the distances of each alternative to the ideal and anti-ideal solutions are:

Distances to the Ideal Solutions

$$d_{a,L05C}^+ = \{0{,}17;\ 0{,}52;\ 1{,}01;\ 0{,}51;\ 1{,}01;\ 0{,}24;\ 1{,}01;\ 1{,}02;\ 0{,}55\}$$

$$d_{a,THT2A}^+ = \{0{,}22;\ 0{,}54;\ 1{,}01;\ 0{,}51;\ 1{,}01;\ 0{,}21;\ 1{,}01;\ 1{,}03;\ 0{,}55\}$$

$$d_{a,L35}^+ = \{0{,}22;\ 0{,}28;\ 0{,}44;\ 0{,}22;\ 0{,}49;\ 0{,}33;\ 0{,}44;\ 0{,}53;\ 0{,}33\}$$

Distances to the Anti-Ideal Solutions

$$d_{a,L05C}^- = \{1{,}01;\ 0{,}55;\ 0{,}14;\ 0{,}54;\ 0{,}17;\ 1{,}01;\ 0{,}14;\ 0{,}10;\ 0{,}51\}$$

$$d_{a,THT2A}^- = \{1{,}01;\ 0{,}54;\ 0{,}15;\ 0{,}55;\ 0{,}22;\ 1{,}02;\ 0{,}15;\ 0{,}10;\ 0{,}51\}$$

$$d_{a,L35}^- = \{0{,}49;\ 0{,}39;\ 0{,}19;\ 0{,}40;\ 0{,}22;\ 0{,}45;\ 0{,}19;\ 0{,}10;\ 0{,}26\}$$

Ranking Alternatives

The final step involves calculating the **relative closeness coefficient**, C_a, of each alternative:

$$C_a = \frac{d_a^+}{d_a^+ + d_a^-} \quad ,\text{for } a = 1, \dots, n$$

This coefficient's value is always **between 0 and 1**. The **closer to 1**, the closer the alternative is to the ideal solution than the anti-ideal one, so **the more preferred** the alternative is.

	Line		
Alternative	**L05C**	**THT2A**	**L35**
PTM	0,86	0,81	0,40
UM	0,52	0,50	0,46
TPM	0,12	0,13	0,33
ITVM	0,52	0,52	0,52
APM	0,14	0,19	0,34
BWM	0,81	0,84	0,33
AM	0,12	0,13	0,33
IBM	0,09	0,09	0,16
SM	0,48	0,48	0,31

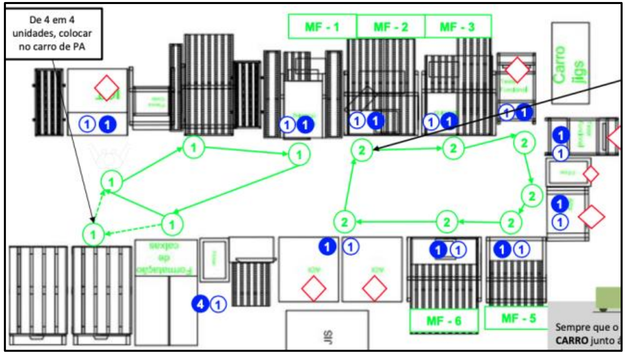
TOPSIS can suffer from **bias due to subjective criteria weighting**. To reduce this impact, the first and second highest-ranked alternative for each line were considered, rather than relying exclusively on the highest-ranked option.

Madanchian & Taherdoost, 2024

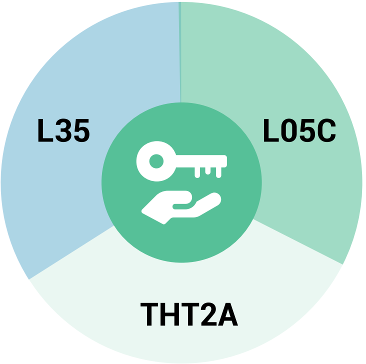
BDMs Selection

UM is less suited for **dynamic systems**

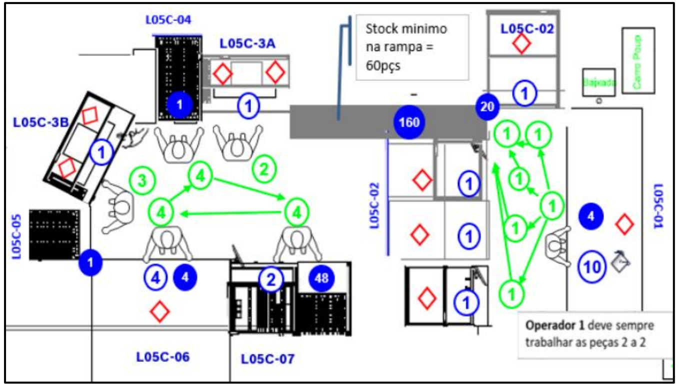
ITVM was selected to best match the system's dynamics



Flow-line dynamics and higher accuracy favor BWM over PTM

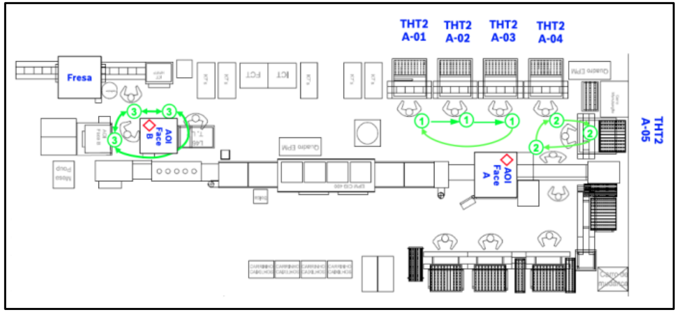


BWM was chosen for its superior performance in terms of accuracy and suitability



BWM discarded due to **lack of defined buffers**

PTM is selected as it does not rely on buffer information and still provides robust insights



Contribution and Future Work

- By integrating systematic decision-making into bottleneck detection, this study provides a replicable framework for industries aiming to improve throughput under different operational constraints;
- Future research could apply alternative MCDM methods, such as AHP or VIKOR, to validate findings and compare outcomes.

Thank you!

Questions ?