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Reduction of The Operational Cost of Sintering Furnace Systems per Configuration (Setup) Through Decision-Tree Sequencing – A Case Study in an Electronics Company in Nuevo León, México

V Lara-Jiménez, JM Hernández-Ramos, C Solís-Peña, J Cuellar-Celestino, and SG Elizondo-Arroyave

Area of Industrial Engineering and Management
School of Chemistry
Universidad Autónoma de Nuevo León,
San Nicolás de los Garza, Nuevo León, México

Corresponding author's Email: valentin.larajm@uanl.edu.mx

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Abstract: Sintering is a heat treatment applied to a powder compact in order to impart strength and integrity. This process relies on sintering furnace systems stability and energy efficiency. However, conventional sequencing control usually lacks consideration of system reliability and costs caused by the configurations/setups actions. The ignition and configuration, as well as the qualification of the product that is decided to process in new furnaces is a long process. Developed parameters of the process of configuration lasts three months, however, non-develop parameters of the configuration takes longer, as a result, operational costs are increased. In order to evaluate the effectiveness sequencing of type batch (B) versus type propane (P) furnace, the experiments are performed with six months of data collection, where the effectiveness and the reliability of the proposed process is verified. The stated objective has been to maximize the expected monetary value (EMV). It is concluded that the propane furnace has an excellent classification performance for high production but also produces a more compact decision tree, than batch furnace.

Keywords: Configuration, Decision Tree, Reliability, Setup

1. Introduction

Organizations must reduce their operating costs to remain competitive. They should focus on the indicators, resources and tools that will help them measure, analyze and manage the type of information relevant to productivity optimization. The overall equipment effectiveness (OEE) is used as an essential quantitative tool for measuring productivity in manufacturing industries (Heng, Aiping, Liyun, & Moroni, 2019). It is designed to identify and analyze the losses of available time of the equipment such as unscheduled stoppages, speed reduction and production losses. Its objective is to provide relevant information for decision making, so organizations can find an area of opportunity to improve the performance and reliability of resources. Key performance indicators (KPI) such as OEE are essential for the management, control and measurement of performance in different areas such as manufacturing, maintenance, planning and programming, product quality, inventory (Teoh, Ito, & Perumal, 2017) , among others.

2. Literature review

The objective of Nakajima (1988) when introducing the concept of Total Productive Maintenance (TPM) was to improve and maintain the efficiency of the equipment. Focusing on maintenance, performance measurement and productivity improvements (Hedman, Subramaniyan, & Almströnm, 2016)**,** (Andersson & Bellgram, 2015).

The basic formula for calculating OEE is:

$$OEE = Availability \times Performance\ efficiency \times Quality\ rate \quad \text{(1) (Nakajima, 1988)}$$

where availability is defined as the ratio of planned production time minus unplanned downtime (breakdowns and setup), during planned production time. Efficiency is the ideal cycle time times the number of products produced at actual run time. The quality rate is the ratio of the accepted products to the number of products produced.

The OEE is affected by the six big losses, which are present in the indicators of availability, performance, efficiency and quality rate (Hedman, Subramaniyan, & Almströnm, 2016)**.**

The availability indicator shows the downtime losses:

- Equipment failures are classified as lost time when productivity is reduced and quantity losses caused by defective products.
- Loss of setup and adjustment time is the result of downtime and defective products that occur when production of one item ends and equipment is adjusted to meet the requirements of another item.

The performance efficiency indicator is formed by the following causes:

- Slow speeds and minor stops losses occur when production is interrupted by a temporary malfunction or when a machine is in warmup.
- Reduced speed losses refer to the difference between the design speed of the equipment and the actual operating speed.

The quality rate indicator shows quality losses such as:

- Reduced performance occurs during the early stages of production from machine startup to stabilization.
- Quality defects and reworking are quality losses caused by malfunction of production equipment.

Setup time are defined as the time required to configure a specific production system to run a different product with all the requirements needed, this activity does not generate value that incurs unproductive costs (Sousa, y otros, 2018) (Goubergen & HV., 2002) (McIntosh, Culley, Gest, Mileham, & Own, 1996) (See Figure 1).

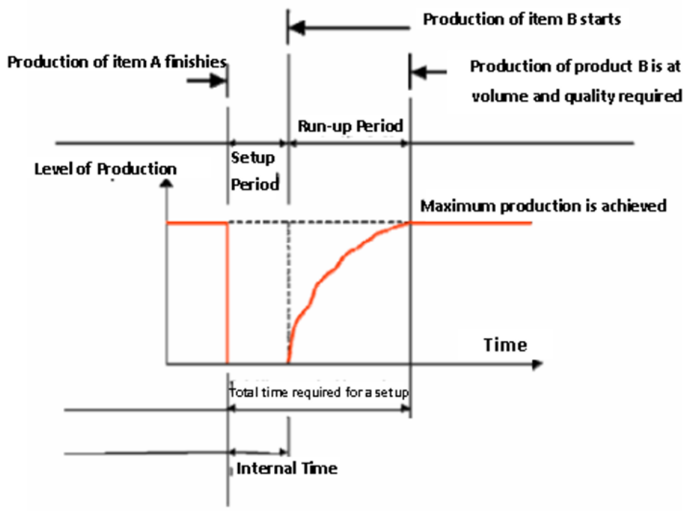

Figure 1. Representation of Setup (Brito, Ramos, Carneiro, & Goncalves, 2017)

Since the configuration of the equipment is not a value-added activity, organizations must find a way to optimize them to reduce operating costs and remain competitive. A correct selection of the size of the product to be processed is necessary in order to incur fewer costs for configurations. Organizations must be supported by tools to help them make decisions.

A decision tree (DT) is a collection of test nodes and terminal nodes, arranged in a tree, structured backwards. Each test node is associated with testing attributes against a value. An attribute is a parameter relevant to the classification problem of interest. Each successor to a test node corresponds to a possible test result. The terminal nodes indicate the class to which the tested state belongs (Van Cutsem, Wehenkel, Pavella, Heilbornn, & Goubin, 1993).

A DT is a form of inductive learning, for a given data set, the objective is to build a model that captures the mechanism that gave rise to the data (Vanfretti & Arava, 2020). DT are grown through a systematic method known as recursive binary partitioning; where successive questions are asked with yes / no answers to divide the sample space (Van Cutsem, Wehenkel, Pavella, Heilbornn, & Goubin, 1993). In order to achieve its goal, researchers are developing different algorithms using expertise from various fields of study (Neto & Castro, 2017).

There is a whole family of DT learning algorithms sometimes referred to as Top Down Induction of Decision Trees, among these, the best known are: ID3, Cart, Assistant Chaid, C4.5 and C5.0 (Castillo Rojas & Meneses Villegas, 2013).

The ID3 and C4.5 are information gain based algorithms developed by Ross Quinlan (1993), the C4.5 algorithm is an improved version of the former one. ID3 algorithm constructs decision trees based on the information gain gotten from the training data, whereas C4.5 uses an additional information called gain ratio. DT are characterized by seeking a completely expressive hypothesis space that avoids the difficulties of restricted hypotheses; and its inductive bias is to prefer small trees to large ones (Hand, Mannila, & Smyth, 2001). DT algorithms such as ID3 and C4.5 have been the most used algorithms for classification. Selecting the optimal coefficient of the combined algorithm in the proposed method significantly improved the classification accuracy and efficiency (Mienye, Sun, & Wang, 2019) (Anuradha & Velmurugan, 2014).

Coolen and Coolen-Maturi (2013) propose the survival signature method for the system reliability analysis, being very useful for parallel redundant systems with multiple types of components and multiple distributions in the production system. The survival signature has the advantage that it can separate the structure of the system from the distribution of the failure time of its components or probability of success (Feng, Patelli, Beer, Beer, & Coolen, 2016). This is useful when it comes to maximizing EMV since what is sought is profitability for the organization; by reducing operating costs, they can remain competitive.

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3. Method

There are two types of furnaces: type B and P furnaces. The equivalencies are different: 1 type P furnace is equivalent to 10 type B furnaces, so due to the increase in demand for product K it was attractive grade it in the type P furnace. In addition, the cost of operating the furnaces is reduced as the quantity of product to be processed by the type P furnace increases. However, the monthly cost of operating a type P furnace is much higher, as shown below:

- 1 Type P furnace = Costs $15,000 USD / month
- 1 Type B furnace = Costs $2,500 USD / month
- Capacity 1 type P furnace = 10 type B furnace

At this point in time, in which the economic situation has changed, it is being decided whether to configure the type P furnace for product K, or we leave the type P furnace for product D, the following was considered:

- Product K has never been processed in a type P furnace and there is a lot of uncertainty in its qualification, while product D has always been processed in furnaces of this type, the probability of success is known = 1
- As long as the volume equivalent to 6 type B furnaces is processed in a type P furnace, we neither lose nor win, it is our breakeven point ($15,000 / $2,500 = 6)
- If we process more than the equivalent of 6 type B furnace in a type P furnace, the cost of the operation is reduced, so it is desirable that the volume is higher than the current requirement of 6 type B furnaces.
- The configuration of product D takes 45 days and costs around $22,500 USD.
- The configuration of product K takes 80 days and costs around $42,500 USD.
- The 6-month contribution margin calculation was made to normalize the periods and because there is no vision beyond 6 months of the demand with certainty.
- The longer the configuration (or qualification) of a product takes, the less production time will be available in the next 6 months.

The Table 1 shows the information of type P furnace collected and its calculation:

Table 1. Type P furnace with product D

	Type P furnace with product D in 6 months	Formula
Days of operation	135 days	=(30 days x 6 months) - 45 days of qualification
Days of qualification (configuration)	45 days	
Cost of type P furnace working per day	$500	
Cost of type P furnace working per month	$15,000	=$500 x 30 days
Cost of qualification	$22,500	=$500 x 45 days
Cost of type P furnace working 6 months	$90,000	=$15,000 x 6 months
Revenue/day	$127,349	Product D historical
Revenue in 6 months (without qualification)	$17,192,115	=$127,349 x 135 days
Operating margin in 6 months	$17,192,115	=($127,349 x 135 days) - $90,000

The Table 2 shows the information of type P and B furnace with product K:

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Table 2. Product K in type B and P furnace

Description	< 6 type B furnace	= 6 type B furnace	> 6 type B furnace
Type B furnace considered	5	6	7
Days of operation in 6 months	100	100	100
Days of qualification of product K	80	80	80
Cost of type P furnace working per day	$500	$500	$500
Cost of type P furnace working per month (30 days)	$15,000	$15,000	$15,000
Cost of type B furnace working per day	$83.33	$83.33	$83.33
Cost of type B furnace working per month (30 days)	$2,500	$2,500	$2,500
Cost of qualification in a type P furnace	$40,000	$40,000	$40,000
Cost of type P furnace working 6 months	$90,000	$90,000	$90,000
Revenue/day of product K	$8,627	$8,627	$8,627
Revenue in 6 months of product K (without qualification)	$4,313,500	$5,176,200	$6,038,900
Operating margin of product K in a type P furnace in 6 months	$4,225,500	$5,086,200	$5,948,900
Operating margin of product K in a type P furnace in 6 months	$7,689,300	$9,227,160	$10,765,020

4. Results

4.1 Qualify product K and D in a type P furnace

The volume of product D is higher than the volume of product K, so it is easier to justify the use of a furnace of this magnitude in this type of product, however, given the increase in demand for product K, we need to evaluate whether or not it is appropriate to use one of these furnaces for product K. The analysis has been done on a 6-month basis (variable costs and revenue in days of operation, discounting the qualification of each product, and the contribution margin of the product has been considered.

4.1.1 Probability of success (reliability)

Considering the following probabilities for analysis based on current data (see table 3):

Table 3. Reliability

Reliability of product D in a type P furnace	1.00
Reliability of product K in a type P furnace	0.70
Probability of requiring the equivalent of 5 type B furnace to process product K	0.40
Probability of requiring the equivalent of 6 type B furnace to process product K	0.35
Probability of requiring the equivalent of 7 type B furnace to process product K	0.25

4.1.2 Costs comparison

The cost of processing product K in a type P (PK) furnace versus cost of processing product K in a type B furnace (BK), were considering that the cost of having a type P furnace on for 1 month is equivalent to having 10 type B furnace on for 1 month, as seen in Figure 2.

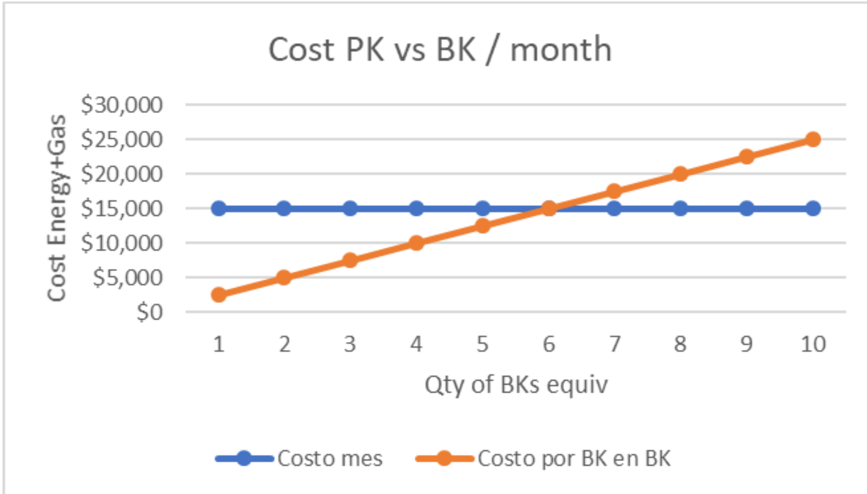

Figure 2. Costs of PK vs BK

4.2 Decision-Tree

We evaluate the sequencing of batch and propane furnace, with product D for type P furnace, the effectiveness and the reliability of the proposed process is verified (see Figure 3).

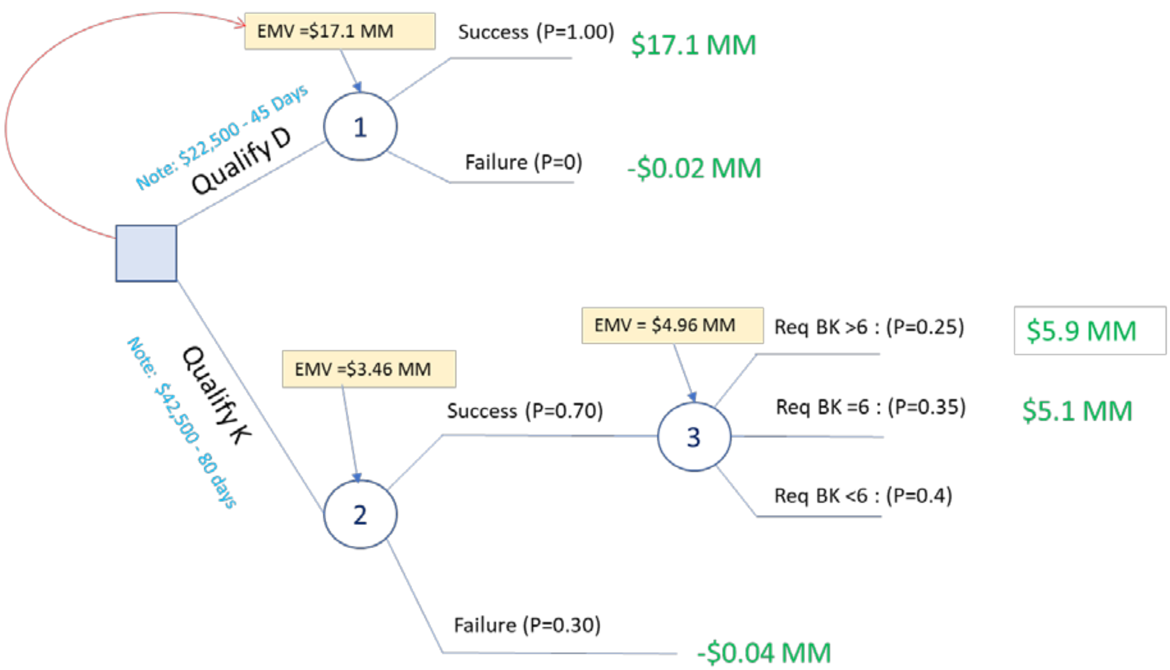

Figure 3. DT of qualifying product K and D in a type P furnace

The stated objective has been to maximax criteria for the EMV, as seen in Table 4.

Table 4. Maximax criteria for EMV

Cost of BK	$2,500 USD/month
Cost of PK	$15,000 USD/month
Revenue KR/ BK	~$8,626.90 day= 258,780 USD/month
Revenue PK	$127,349.27 USD/day
Revenue PK in 6 months (135 days)	$17,192,151.45 USD

5. Conclusions

It has been decided to grade product D in a new type P furnace due to the following:

- The highest EMV occurs under this condition (contribution margin of 17 million dollars in 6 months).
- The probability of success with this product is known.
- The market has changed and product K currently requires 1 type B furnace, so operating costs would be considerably higher if processed in a type P furnace.
- Progress has been made in a K product prequalification in a type P furnace to have platform flexibility when the volume of this product increases.
- Material K in a type P furnace showed to have a very reduced process window with respect to product D or with respect to a type B furnace.

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