

IMPACT OF COVID-19 PANDEMIC ON THE EFFECTIVENESS OF AUTOMOTIVE PRODUCTION LINES-CASE STUDY

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Abstract

Since its discovery, the COVID-19 virus spread all over the world and caused millions of deaths, this paper focuses on studying the impact of the pandemic on the connected and non-connected automotive production lines. This study is developed on two production lines in an automotive manufacturing factory that assembles 700 cars per day and the study is elaborated following two main steps: firstly, studying the impact of the virus spreading on the OEE “Overall Equipment Effectiveness” of the production lines, which is a quantitative metric used for the evaluation of the line effectiveness based on availability, performance and quality, and secondly analyzing the relationship between these factors and the OEE using the Design of Experiments method.

Keywords: COVID-19, Connected Production Line, Non-Connected Production Line, Overall Equipment Effectiveness, Design of Experiments

Introduction

“The ongoing Coronavirus disease (COVID-19), caused by the SARS-CoV-2 virus, was first identified in December 2019 in the Chinese city of Wuhan, and was declared a global pandemic by the World Health Organization” (WHO, 2020), and at the time this article was written, there were more than 6 million fatalities and more than 580 million confirmed cases globally. COVID-19 is not just a global pandemic or disease that impacts the health of the human being, it has affected also the global economy and financial markets, and one of the sectors affected by the virus is the automotive industry. Companies of this industry have reduced

the import of raw materials, lowered sales, decreased production capacity, decreased order demand, and significantly decreased sales turnover (Purwanto *et al.*, 2020). As disease outbreaks are unlikely to stop in the foreseeable future, thorough research and preemptive measures are needed to not only save lives but also safeguard the economy. (Pak *et al.*, 2020). This led us to conduct a study to analyze the impact of the pandemic on automotive production lines, by studying the direct impact of the virus on a manual non-connected line and compare it to the impact on a connected line in the same factory under the same conditions. To make an

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overall comparison, the proposed comparison metric is the Overall Equipment Effectiveness (OEE) proposed by (Nakajima, 1988); which is used for measuring the productivity of equipment and production lines. It identifies and measures losses of important aspects of manufacturing namely availability, performance, and quality rate (Williamson, 2006). This paper reviews related articles on production lines, covid-19 pandemic and OEE measurement tool in Section 2. Section 3 is describing the methodology of this study. Findings and results of the OEE calculations are presented in Section 4 and discussed in Section 5. Finally, the Section 6 concludes this study.

Literature review

Production lines

The industrial world has had four industrial revolutions up to the present, all of which had a favorable effect on the world economy. Due to the aforementioned industrial revolutions, various industrial tools have undergone numerous alterations. (EL ABBADI *et al.*, 2020) .

Since the first industrial revolution, manufactured goods were handmade by individual workers in independent workshops, each worker creates his own part using only manual tools, and the final product was assembled at the end, the production lines were fully manual (Corday, 2014). After the start of the second industrial revolution at the end of the 19th century, Henry Ford installed the first non-connected production line exactly in 1913, which can be defined as a group of workstations aligned in a serial manner where the work pieces visit stations successively either manually or by a transportation system, e.g. a conveyor belt, without any connection or link between machines (Boysen *et al.*, 2007; El Ahmadi and El Abbadi, 2022), the worker assigned to the workstation ws_i is communicating with the workers of ws_{i-1} and ws_{i+1} to ask about the progress of their operations in order to avoid starving or blocking the production line.

In 2010, the German government starts talking about the smart factory, which is a flexible system that can self-optimize the performance and self-adapt to new conditions, it consists on a structure of machines, facilities or resources and a communication network (Meng *et al.*, 2018). Machines exchange information and sensors send signals through the network to the cloud. In the cloud, data are analyzed with machine learning techniques and other information technologies, after, these results or predictions are sent to terminals for making decisions so that the

supervisor can decide to make adjustments to the facility in advance, which reduces the risk of accidents or failures and avoids energy waste (Meng *et al.*, 2018). In other words, the smart factory concept is the heart of the industry 4.0 (Mabkhot *et al.*, 2018).

The Henry Ford non-connected line is to be replaced by a new fully connected line that is made up of a collection of workstations connected via a connected network employing a combination of information, production, and communication technologies (RFID sensors, digital workstations and automatic guided vehicles) (EL AHMADI & EL ABBADI, 2020).

COVID-19

At the end of December 2019, an outbreak of unknown pneumonia was reported in Wuhan, Hubei province, China (Zhu *et al.*, 2020). The World Health Organization issued a Public Health Emergency of International Concern on January 30, 2020, and on March 11, 2020, COVID-19 was identified as a Pandemic that has since swiftly spread throughout the world. (WHO, 2020).

Due to early fatalities, decreased productivity at work, and factory closures, the COVID-19 pandemic has had a direct detrimental influence on the world economy. It has also created a negative supply shock, which has slowed down manufacturing activity. (Pak *et al.*, 2020)

OEE Measurement Tool

The OEE was first introduced by Nakajima as a metric or measure for the evaluation of equipment effectiveness, and according to Williamson, it measures how well a piece of equipment performs its intended function based on availability, performance, and quality rate (Nakajima, 1988; Williamson, 2006).

The OEE was initially a key element of TPM and was used to boost production line productivity and decrease time, speed, and quality losses. OEE aims to detect all production losses, in other words, which according to (Ericsson, 1998; Klimecka-Tatar & Ingaldi, 2022) are losses that make up a significant amount of the entire cost of production and can be divided into six major categories, as shown in Tab. 1: As shown in the Tab. 1, every OEE factor is connected to a specific loss category which generates many possible types of loss, these losses are expressed as a function of several mutually incompatible factors. (Huang *et al.*, 2003):

Availability (A)

The availability factor calculates the entire amount of time the system is not in use due to (Patel and Deshpande, 2016) malfunctions, setup,

adjustments, and other halts. (Jonsson and Lesshammar, 1999), in another perspective it is a measure of how big the downtime losses are (Ngadiman *et al.*, 2013)

$$A = \frac{LT - DT}{LT} \quad (1)$$

- LT: Loading time
- DT: Down time

Performance (P)

A production cycle involves the transformation of inputs into output. Equipment should operate as quickly as the output of the theoretical production, in theory. However, in practice, this is not achievable because there may be numerous obstacles that prevent the equipment from operating as it should. (Ngadiman *et al.*, 2013). According to (Jonsson and Lesshammar, 1999; Muñoz-Villamizar *et al.*, 2018), the performance factor measures the ratio of the real speed of the equipment to the ideal theoretical speed and according to (Nakajima, 1988), the performance factor can be computed using the formula below:

$$P = \frac{ICT \times OP}{OT} \quad (2)$$

- ICT: Ideal cycle time, it refers to the theoretical cycle time of the line
- OP: Output
- OT: Operating time, it is the time that the equipment is working (producing units)

$$OT = LT - DT \quad (3)$$

Quality (Q)

The quality factor represents the percentage of defective units to the total units produced in the line.

According to (Nakajima, 1988) the quality factor involves only defective units that occur in that designated stage of production, usually on a specific machine or production line and not anywhere in the factory. This factor is calculated using the following formula.

$$Q = \frac{TP - DU}{TP} \quad (4)$$

- TP: total production, it refers to the total number of products.
- OT: Defective units, it refers to the number of defective units

In essence, OEE is the result achieved by multiplying these three factors together as shown by the Nakajima's formula (see Table 1).

$$OEE = A \times P \times Q \quad (5)$$

Analytically, OEE can be expressed as the ratio between what was actually manufactured and what could be ideally manufactured. According to (Kristina, 2014), the OEE of production lines can be compared worldwide as shown in the Figure 1.



Figure 1. Classification of OEE

Table 1. The Six big OEE losses

OEE Factor	Loss Category	Loss Type	Event
Availability	Down time Loss	Breakdowns	Tooling mistakes Nonplanned maintenance Production line Failure
		Setup	Changeover Major adjustments Warm-up Time Material shortages
Performance	Speed Loss	Speed loss	Equipment Wear Operator inefficiency Under design capacity
		Small stops	Sensor blocked Product flow blocked Cleaning / Checking
Quality	Quality Loss	Production Rejects	Scrap In Process Damage
		Start-up Rejects	Scrap Rework Damage

Methods and Materials

An automotive production line typically starts with the bare chassis (the basic component of a car), and then the other components are assembled successively. In the automotive industry, the vehicle typically passes by the stamp department, body department, painting department, and finally the assembly department where our study took place (the engine, battery, drive axle, steering wheel, windows) (EL AHMADI & EL ABBADI, 2022).

Presentation of the studied lines

The assembly department is composed of 6 production lines: SE2, SE4, MO1, MO3, SC5 and PO4, but SE2 and PO4 are the only two lines assembling the same pieces and having the same flow time and same conditions, this is the reason of choosing these two lines for our case study.

The SE2 manual, non-connected production line includes 11 workstations, 20 workers (both sides at each workstation), and 2 quality control operators who assemble the interior components of the car (accelerator pedal, brake, glove box, right seat, seat belt, hand brake, steering wheel, etc.) (as shown in Figure 2).

PO4 is a connected production line composed also of 11 workstations but all the assembly operations are performed by robots and machines and the transportation operations by the automatic guided vehicles, the same interior pieces assembled in SE2 are assembled in this line (as shown in Figure 3).

Research methodology

To study the impact of COVID-19 pandemic on the two studied lines, the proposed methodology

in this article is based on the calculation of the OEE of the lines and compare and analyze the results using the design of experiments method.

To calculate the OEE, data were collected from a 2 years data extraction from a CPMS (Computerized Production Management System) called JDE Oracle over two different periods

- Period 1: February 2019 - February 2020 (Before COVID period)
- Period 2: February 2020 - February 2021 (During COVID period)

Data collected are

- Loading time
- Downtime
- Number of defective units
- Setup time
- Downtime

Then the OEE factors (Availability, Performance, Quality) are calculated using the formulas (1-5) to calculate finally the OEE level for each period.

Results

As shown in Figure 4, the COVID pandemic had a negative influence on the performance factor, which dropped from 89% to 72%. The availability factor was also affected and dropped by over 11,6%, while the quality rate was slightly affected.

The OEE factors in the connected line have not decreased as shown in Figure 5.

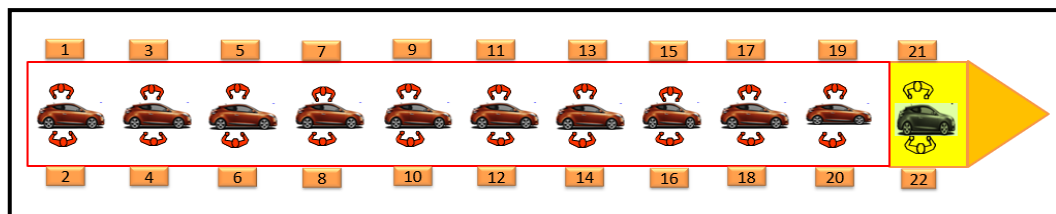


Figure 2. Non-Connected Line SE2

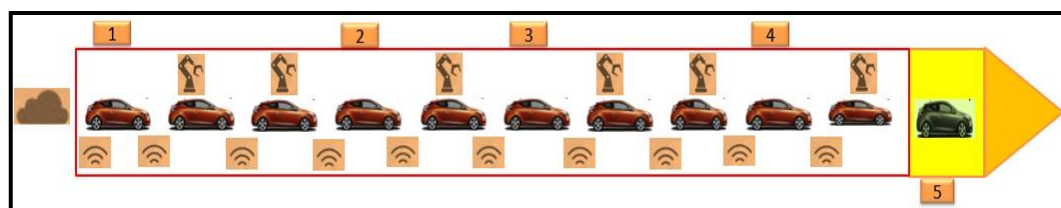


Figure 3. Connected Line PO4

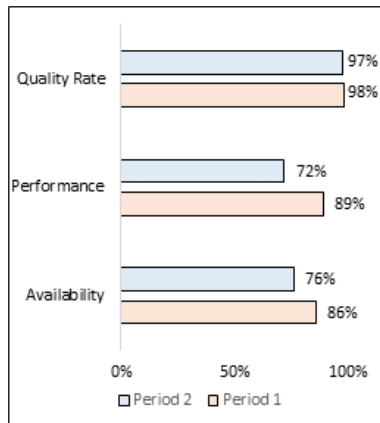


Figure 4. Comparison of OEE factors between before and during COVID periods in SE2 line (non connected)

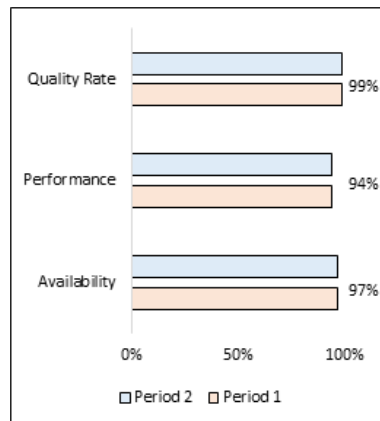


Figure 5. Comparison of OEE factors between before and during COVID periods in SE2 line (connected)

The analysis reveals stability in the connected line PO4. However, in the non-connected line SE2, the decrease in the three OEE factors resulted in a significant decrease in the efficiency of the line (-30%) going from 75% to 53% in only 1 year, and this was expected because during the pandemic, many shutdowns occurred in all non-connected lines in the factory due to lack of workers, shortage of raw materials, restricted movements and many other reasons, more analysis should be done to find the factor that has more impact on the OEE (as shown in Figure 6).

Discussion

To analyze the impact of each of the factors (performance, quality and availability) on the OEE

of the non-connected line, the use of Design of experiment (DOE) is important, a full factorial design is done using MiniTab 19 software, the experiment is designed for 3 factors (A, P and Q) and 2 levels for each factor (as shown in Table 2):

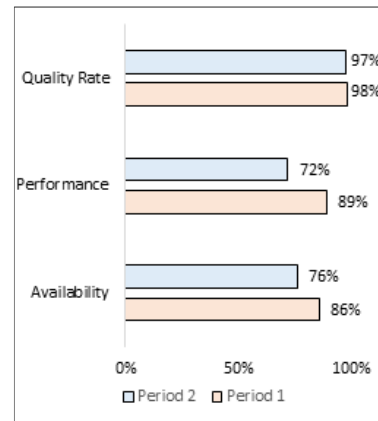


Figure 6. Comparison of OEE between before and during COVID periods

Table 2. Experimental setup for DOE

A (%)	P (%)	Q (%)	OEE (%)
72,0	70,0	97,6	49,2
72,0	70,0	97,9	49,3
72,0	74,0	97,6	52,0
72,0	74,0	97,9	52,2
80,0	70,0	97,6	54,7
80,0	70,0	97,9	54,8
80,0	74,0	97,6	57,8
80,0	74,0	97,9	58,0

For estimating the relationships between the outcome variable “OEE” and the predictors “A, P and Q”, a regression analysis is elaborated as “OEE versus A, P and Q” after checking the validity of regression assumptions.

Instead of performing the experimental activity at levels other than those on the Tab 3, regression equations can be useful in estimating the process output parameter. (El-Mahalawy *et al.*, 2021). For prediction and forecasting, it is utilized to determine the relationship between the control and response parameters (Tonidandel and LeBreton, 2011). Equation (6). is the generated regression equation to predict the OEE at any availability, performance or quality value.

The regression equation is:

$$OEE = -1,07 + 0,70380 \times A + 0,7429 \times P + 0,547 \times Q \quad (6)$$

The compatibility between the observed data and what we would anticipate or forecast if we knew the complete statistical model were true is statistically summarized by the P-value. (Greenland *et al.*, 2016), in other words it allows you to check if the relationships you detect in your sample are present in the larger population. In our case the p-value analysis shows that there is a significant linear relationship between A, P and OEE because their p-values equal 0.000, while the quality rate is not statistically significant (as shown in Tables 3, 4 and 5).

Table 3. Variables and its coefficients and significance value

A (%)	P (%)	Q (%)	OEE (%)
72,0	70,0	97,6	49,2
72,0	70,0	97,9	49,3
72,0	74,0	97,6	52,0
72,0	74,0	97,9	52,2
80,0	70,0	97,6	54,7
80,0	70,0	97,9	54,8
80,0	74,0	97,6	57,8
80,0	74,0	97,9	58,0

Table 4. Estimated Coefficients for OEE using data in coded units

Term	Coef
Cons	0,53
A	-0,03
P	-0,01
Q	-0,00
A*P	0,00
A*Q	0,00
P*Q	0,00
A*P*Q	-0,00

Table 5. Analysis of Variance

Source	DF	Adj SS	Adj MS	P-Value
Regression	3	0,008	0,003	0,000
Error	4	0,000	0,000	-
Total	7	0,008	-	-

Table 6. Ranking of factors

Source	DF	Adj SS
A	1	0,006
P	1	0,002
Q	1	0,000

According to the ranking of factors in Table 6, the quality rate is the less impacting factor on the OEE (Adj SS= 0.000005), and this is logic because in the automotive industry, the quality is not a major problem and the rejection rate is very low, so in the following analysis, the quality rate is fixed (Q=97,75%) and we plot using Minitab19 a contour

& a surface plot of the values with respect to the availability and the performance factors.

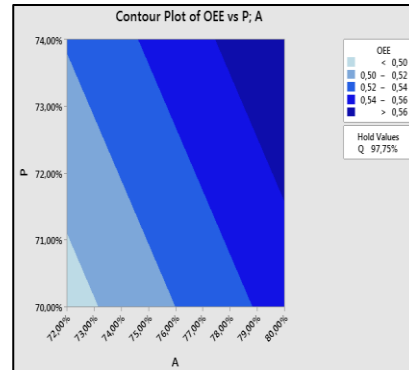


Figure 7. Contour Plots of OEE Vs A and P

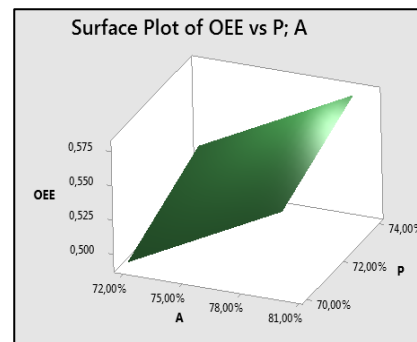


Figure 8. Surface plots of OEE Vs A and P

The contour plot (called also level plots) of OEE Vs A and P factors shows the relationship between the availability and performance factors and how they influence on the OEE, darker regions in the contour plots indicate high OEE (greater than 56%).

As seen in Figure 7, On the x-axis, if you start with an availability of 72% and increase it by 1%, the OEE increases directly from 50% to 56%. On the other hand, if you start on the y-axis with a performance rate of 70% and increase each time by 1%, the OEE wouldn't exceed 52% except if the availability increases also, this analysis confirms that the linear relationship between the availability and the OEE is more significant.

The surface plots of OEE vs A and P factors uses a 3D surface to see how the OEE relates to A and P factors, the peak on the plot corresponds with the highest OEE, and occurs at approximately A=80% and P=74% (as shown in Figure 8).

The regression analysis gives a classic equation of OEE and many other analyses of the

factors and it shows that OEE will be significantly improved by giving focus to the availability factor improvement.

In order to improve the non-connected line availability, three main solutions are proposed:

- Industrial Internet of Things
- Worker upgrading and requalification
- Respect of sanitary rules inside the factory

Conclusion

The effectiveness analysis of the two studied lines showed that the OEE of the non-connected production line have decreased from 75% before the pandemic to 53% during the pandemic while the OEE of the connected production line remained stable and didn't decrease.

The non-connected automotive assembly process is not immune to the propagation of COVID-19, and it would not resist to any future natural outbreak, and any infectious virus can impact the effectiveness of the manual and non-connected lines negatively because the human factor is very sensitive in this case.

Design of experiments and regression analysis are done using MiniTab 19 software and reveals that the availability factor is the OEE factor that has the priority and more impact on the non-connected line effectiveness.

Three solutions are proposed in order to improve the availability factor: The industrial internet of things, worker upgrading and requalification and the respect of sanitary rules inside the factory.

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