Implementing the Concept of Alarm Flexibility During Production

Hamza Ahmad khan1*, Ihtisham Ul Haq1, Zubair Ahmad khan1, and Azhar Qazi2,

1Department of Mechatronics Engineering, University of Engineering & Technology Peshawar, Pakistan
2Department of Electrical Engineering, CECOS University Peshawar, Pakistan

Corresponding author: Hamza Ahmad khan (e-mail: hamzaahmad.mct@uetpeshawar.edu.pk).

Received: 05/06/2022, Revised: 01/09/2022, Accepted: 20/09/2022

Abstract- An interruption at a workstation is a major cause of production downtime, negatively affecting performance, cost, consumer-centric value, and efficiency. Blockage and starvation brought on by broken workstations have a domino effect on the entire production line. To allocate resources effectively and minimize downtime, it is crucial to analyze each disruption's effects thoroughly. Quantitative analysis of disruption at a single workstation and its effects on neighbouring workstations are performed in work presented. Faulty workstations have an additional threshold value added to the Alarm Trip Point (ATP), depending on their current state. This one significantly improves upon downtime mitigation and batch rejection reduction compared to previous approaches. A more general model based on multiple workstations has been developed by expanding the analysis for a single workstation. The proposed work is demonstrated in an experimental case study, an Asphalt-Processing Plant. It is applied in addition to developing a theoretical model to reduce downtime, multiple starts and stops, and numerous rejections. The proposed method reduces start-stop events by 60%, reducing rejections and downtime while increasing consumer-centric value and efficiency.

Index Terms—Manufacturing process, alarm trip point, and disruption process.

I. INTRODUCTION

The overall efficiency of a manufacturing process suffers whenever there are interruptions in any automated processes involved. There are a wide variety of instantaneous disruptions that can affect dynamic manufacturing processes [1]. Machine failure, broken tools, improper sensor calibration, cancelled orders, etc., all fall into this category of interruptions. The machine shop is the nerve center of a factory because of the important decisions it makes in real time to boost output, cut costs, and focus on customers. To properly allocate resources and prioritize projects, knowing how much it will cost to have disruptions must be a top priority. To save money, maintain financial stability, and prioritize the needs of customers, it’s important to conduct a thorough disruption analysis.

Identifying the monetary value of each disruption is essential. Several stations are used in a multistage production system, either in a sequential fashion or in parallel with one another, and buffers separate them. Several operations are planned to occur in a specific order, leading to the final product. All subsequent operations at other stations are impacted by blockage and starvation if one stage is delayed or disrupted (upstream or downstream). Maintenance and repair costs, technical costs, the cost of newly fitted parts, operational costs (direct costs such as equipment and operator wages), and idle workstations all factor into the total cost of disruption.

During a disruption or downtime incident, it is easy to divide up the cost of operations and maintenance. However, it can be challenging to allocate collateral costs in systems with unsynchronized operations and those separated by finite buffers, such as multistage production systems. Instead, the distribution of collateral costs is simple in a perfectly synchronized system. Because of the buffers, the disruption takes longer to spread from one computer to another. Since this is the case, the first step in calculating the secondary loss is to evaluate each interruption's effect on the production line.

Measuring the effect of disruptions that lead to downtime in manufacturing presents unique challenges for each manufacturing process. First, it is difficult to link the downtime and financial and production costs of one station's blockage and starvation to the downtime and costs at other stations. To properly evaluate these associations, it is necessary to identify the underlying causes of both blockage and starvation. Second, it is unclear how long an interruption in the production line will last. Production at other stations may temporarily slow down or cease altogether due to disruptions at other stations. Although production drops off sharply during disruptions, it is possible to get back to normal once the situation has stabilized. Since only those stations are considered when calculating the disruption price, the resulting downtime and expenses are permanent.

Here is how the rest of the paper is structured: The paper is divided into six sections: an introduction (section 1), a literature
II. LITERATURE REVIEW

Over the past few decades, there has been extensive study [2]-[4] on how the performance of unreliable stations and finite buffers in the manufacturing process affects downtime and efficiency. A lot of study has been dedicated to the fundamental problem of machinery failure. The proposed method is analyzed in detail on a production system with seven workstations in a paper by Gupta [5]. Performances of FKS (Flexible Kanban System) and TKS (Traditional Kanban System) were comparable in terms of product quantity and completion time in the event of a disruption or machine breakdown. Shin [6] calculated how a machine failure would affect the overall system throughput. However, the tasks are completed in a fashion analogous to a production line simulation. Wazed et al. [7] looked into the effects of machine failure on production efficiency, the batch size on output, and the length of time it takes to complete a single production cycle. The ARENA programme [8] models the two separate manufacturing lines. Liar looked into the efficiency loss that occurs when broken machines are repaired or replaced [9]. Wang et al. [10] present a review of alarm configuration based on the proactive establishment of a relationship between process variables, abnormal situations, and process knowledge. The agent-based fault-tolerant framework studied by Zubair et al. [11] effectively deals with disruptions thanks to the dynamic assignment of proper weight to each fault bit and the generation of a response based on the weight vector. The Reliability and Conditioned Based Maintenance methodology, reported extensively in the literature [6, 12]–[14], focuses on identifying and interpreting symptoms of disruption rather than identifying and interpreting how the disruption impacts process flow and efficiency. A design approach for quantifying the effects of disruptions on related workflows has been presented by Pandey et al. [15]. Their model includes alerts that can be used to help with decision-making. Several research groups have developed joint maintenance schemes and inventory control [16]–[18] to deal with unexpected machine breakdowns and keep production from being disrupted. Issues with scheduling caused by machines being unavailable, broken, or undergoing maintenance have been reported previously [19], [20]. Using information about plant activities and variable conditions, Musulin et al. [21] address disruption and risk assessment with reactive, dynamic, online methods. In [4], [22], and [23], researchers examine the transition (transient) of buffer level from a probability distribution to a stationary distribution. Here, Bernoulli lines [4] pinpoint fluctuations in process stockpile and output velocity. The dynamics of the assembly line are carefully analyzed in this method. However, the method cannot reveal how much downtime has impacted system performance. In conclusion, the cost is affected differently by downtime due to factors such as duration (time), buffer levels, and machine location. The abrupt disruption in the transfer line is the basis for the Meta-Model proposed in [25]. To fix the problem, this paper proposes using a delayed exponential function of the first order (continuous). We present a thorough analysis of the bottleneck [1, 24]. In practice, this analysis aids in the judgement calls by plant floor supervisors. Many studies have also been aimed at improving trip point methods. Trigger points for a procedure are often called alarm trip points (ATPs). Because of their significance to the manufacturing process's efficiency and safety, these trip points are widely discussed in the literature [24], [26], and [27]. Most alarm systems conform, and they all have critical settings like alarm limits and alarm thresholds. Henningsen and Kemmerer [26] briefly improved ATPs in a time-variant manner, tailoring the adjustments to the process variables at various stages of operation. In [28], we see how optimal ATPs can be created using only one process variable. The alarm probability plot is created using Markov's chain theory. It contains four statistics based on transition, and the averaged transition step toward and away from an ATP. With the help of the discriminant function of the four statistics we've defined, we can pick the best ATPs for the job. The approach is evaluated by looking at real-world applications in the business world. A new dimension for ATPs was introduced by Hugo [29]. He employs a mathematical handling technique to determine alarm trip point values from the logistic relationship among multivariable. Pre-alarms are recommended in a study of nuclear power plant supervision [27]. When a problem is detected, an alarm sounds and the operator is alerted immediately. To determine the threshold, this system compares normal and abnormal information. Xu et al. have looked into to detect anomalies with fuzzy logic. Study in [30] based on the evidence theory. By deploying a non-linear stochastic model of the entire system [17], Y. Yu et al. [26] have developed a flexible model for ATPs, in which an algorithm is introduced for ATP via data. Information from non-linear processes is manageable by this system. This method reliably anticipates the appearance of delays. Analysis of how downtime at individual workstations affects the whole production line is at the heart of this method. The developed model can assess the potential effect of a disturbance on neighbouring workstations, whether they are currently idle or in a transitional state. A threshold value is calculated that considers the effect that disruption will have on the overall process efficiency based on the status of neighbouring workstations. The alarm trip point (ATP) boundaries are increased by adding the threshold value to the trip points of the affected workstation; this either causes the system to maintain its current status or causes it to operate within the bounds established by the control logic.

III. METHODOLOGY

The proposed method provides options for suspending operations in the event of an impending system failure. However, the overall impact on the process whenever a fault occurs is sometimes ignored by the ATPs defined by various techniques [26][31]. The loss of a valuable batch in progress is inevitable when a process line is tripped due to a fault. Tripping also has secondary negative effects, such as increased downtime and labour costs.
The ATPs found in the scientific literature serve as a starting point for the proposed model. We keep a close eye on the workstations and any side effects or dependencies they may have. In addition, the cumulative process flow and downtime and the effects of disruptions are also analyzed. The overall productivity of the process takes a serious hit due to the workstations. Furthermore, the process's current state determines the appropriate weighting.

Let the value of an analogue process parameter in industrial plants at \( t \) be denoted by \( x(n) \), where \( n \) is a positive integer. The integer \( n \) denotes the sample index in this case. Typically, alarms in an industrial setting are recorded by linking the \( x(n) \) state to a fixed value called the trip value \([26]\). The alarming variable, \( x(n) \), is calculated by comparing the ATP to the current value of \( x(n) \).

\[
\text{Alarm} = 1 \text{ if } x(n) \geq x_{tp} \\
\text{Alarm} = 0 \text{ if } x(n) \leq x_{tp}
\]

In the current setup, the process is halted, and the whole plant is shut down until the fault has been rectified if the alarm value exceeds a certain threshold value (pre-defined in the fault register). Because the entire batch is rejected, this procedure has a major impact on the productivity of the process. In the end, this resulted in high operating expenses and diminished value for the customer. The ATPs are multiplied by a factor called \( \text{thr}(i) \) to combat this fundamental issue (threshold value). This case, the value of "\( \text{thr}(i) \)" depends on the current states of the neighbouring computers (i.e., before and after the faulty station).

\[
\text{Alarm} = 1 \text{ if } x(n) \geq x_{tp} + \text{thr}(i)
\]

The addition of \( \text{thr}(i) \) provides more leeway in the procedure. The process will continue as long as \( x_{tp} + \text{thr}(i) \) is below. The process's overall health is weighed in determining this cutoff value.

A. LOCATING THE WORKPLACES

Each step of the process has been assigned a unique station number. The proposed model views the factory as a network of workstations, some connected in series while others set up in parallel. Any hiccup at any of the stations can potentially halt production in its tracks. Position 1 is the workstation in the process line where the disruption was first detected (at zero). The preceding and subsequent workstations have been assigned the appropriate numbers for the problematic workstation. Figure 1 is a block diagram that depicts several different types of workstations. Any station interruption will disrupt the entire workflow. In Fig. 1, for instance, we see the production procedure. The affected workstation has been labelled WS1, and adjacent workstations are designated by their positions in the office. This disruption has an obvious and immediate effect on stations 1 (causing congestion) and 3. (starvation). Limitation or starting point When determining \( \text{thr}(i) \), the state of the neighbouring nodes is considered. To achieve a range of trip points, the equation shows that the threshold value is added to or subtracted from the defined trip point \([3]\).

\[
\text{Thr}(i) = (T - \delta)MPs(k)
\]

Considering all workstations,

\[
\text{Thr}(i) = \left(\sum_{k=i-\delta}^{i+\delta}(T - \delta)MPs(k)\right)
\]

To arrive at the final result for ATP, the threshold value is added to Equation 1.

\[
\text{Alarm} = 1, \text{ if } x(n) \geq x_{tp} + \left(\sum_{k=i-\delta}^{i+\delta}(T - \delta)MPs(k)\right)
\]

The effect of threshold value \( \text{Thr}(i) \) on the set of ATPs is illustrated in equation (6). By reducing the rejection value, we can save time and money and thus optimize the entire process by determining this value.
C. DIFFERENT CASES DISCUSSED

The first scenario involves a solitary computer calculating the significance of the threshold value, Thr(i) (WS2). The five stations of a manufacturing process are depicted in Fig. 2. Hypothetically, WS1 has been compromised, leading to ATP activation. When the alarm sounds, production at the station and along the assembly line is immediately halted, and the entire batch is thrown away. Thr(i), a threshold value central to the model presented here, determines whether the process is terminated or allowed to continue for a while. Since there is only one neighbouring workstation to WS1, the tuning parameter is set to 1 (=1). The value of Thr(1) is 1 because MPs ((k))=1 when WS2 is operational.

In this situation, (3) implies that the ATP will be increased because there is only one WS2 in play.

when (alarm=1)x(n)>xtp+1. In Scenario 2, the manufacturing process is the same except that the under-consideration workstation WS2 is not in use (Fig. 3). The values of MPs ((k)) and Thr(i) are both 0 in this situation. Disruption at WS1 in the same manufacturing process is depicted in Fig. 3 below, along with a nonfunctional WS2 close proximity (stopped or finished its job). Another time where a zero-threshold value does not alter the alarm value. Values for all possible combinations of thresholds are calculated similarly (see Table I).

In the case of the local workstation, the process will resume its state if the threshold value Thr(i) rises above two, as shown in Table I. The proposed model keeps going when the ATP concentration drops below a certain threshold value, Thr(i), but it stops when the ATP concentration drops below Thr(1). Non-zero threshold values show that the proposed model enlarges the alarm boundaries, where stopping the process results in batch waste, capital loss, downtime, and human labour. Table II displays the threshold values for the various combinations of disruptions if two workstations are considered (right/left) adjacent to a disruptive workstation (value of = 2 and = 2).

| Table I: Threshold value for all possibility | | | |
| Disruptive (WS) | Adjacent (WS) | States | Combinations | Threshold |
| WS1 | WS2 | 00 | 0 |
| WS2 | WS1 | 00 | 0 |

| Table II: Threshold value for WS5 with δ=2 and Γ=2 | | | |
| Disruptive (WS) | Adjacent (WS) | States | Combinations | Threshold |
| WS1 | WS2 | 00 | 0 |
| WS2 | WS1 | 00 | 0 |

FIGURE 1: Error at WS1 in the manufacturing process

FIGURE 2: Manufacturing process with WS2 operational

FIGURE 3: Error at WS1 in the manufacturing process

TABLE II: Threshold value for WS5 with δ=2 and Γ=2

| Disruptive (WS) | Adjacent (WS) | States | Combinations | Threshold |
| WS1 | WS2 | 00 | 0 |
| WS2 | WS1 | 00 | 0 |
The table below does the same for faults in WS3 and WS4, showing all possible combinations of outages. As a result of the permutations and combinations analysis, 15 threshold values are generated for WS3 and WS4. It is only possible for Thr(1)1 to occur when all of the neighbouring computers are not in use. A threshold value of 4 may be used. Rejection costs would be much higher than the cost of upkeep and fixing. Finally, we consider a third and similar to WS1 scenario involving WS5. There is only one neighbouring workstation here, and that's WS4. The generated threshold values are consistent with those shown in Table I.

V. TESTING IN AN EXPERIMENTAL ENVIRONMENT

The proposed method is tested in an Asphalt production facility, which serves as the test rig. As can be seen in Figure 4, this asphalt plant is of the batch mix variety. This structure integrates multiple (mechanical, electronic, and control) subsystems. After the gravel has cooled, it is crushed, then heated to dry the aggregates. Hot asphalt is then combined with the dried aggregate. There are essentially three distinct varieties of asphalt plant: (1) the Batch Asphalt Plant, (2) the Drum Asphalt Plant (with the continuous flow), and (3) the Drum Mix Asphalt Plant. In this investigation, a Batch Asphalt Plant was used to produce asphalt.

A. OVERVIEW OF THE PROCESS

After being stored in cold bins, unheated aggregates are weighed at cold-feed gates leading to a bucket elevator or conveyor. The aggregates are transported to the dryer, where they are dried using heat. The dryer’s exhaust is routed to an exhaust stack and dust collectors, where it is captured and processed. After being dried and heated, the aggregates are transferred via hot elevator to the screening unit, sorted by size and stored in hot bins (temporary storage). When needed, the heated bins release measured amounts into the weigh box. The aggregates and the required quantity of binder (bitumen) are then dumped into the pugmill. The asphalt is then transferred for delivery once it is ready. All of this can be seen in Fig. 4. The process-based categorization of the six WSs depicted in Fig. 5.

The table below does the same for faults in WS3 and WS4, showing all possible combinations of outages. As a result of the permutations and combinations analysis, 15 threshold values are generated for WS3 and WS4. It is only possible for Thr(1)1 to occur when all of the neighbouring computers are not in use. A threshold value of 4 may be used. Rejection costs would be much higher than the cost of upkeep and fixing. Finally, we consider a third and similar to WS1 scenario involving WS5. There is only one neighbouring workstation here, and that’s WS4. The generated threshold values are consistent with those shown in Table I.

V. TESTING IN AN EXPERIMENTAL ENVIRONMENT

The proposed method is tested in an Asphalt production facility, which serves as the test rig. As can be seen in Figure 4, this asphalt plant is of the batch mix variety. This structure integrates multiple (mechanical, electronic, and control) subsystems. After the gravel has cooled, it is crushed, then heated to dry the aggregates. Hot asphalt is then combined with the dried aggregate. There are essentially three distinct varieties of asphalt plant: (1) the Batch Asphalt Plant, (2) the Drum Asphalt Plant (with the continuous flow), and (3) the Drum Mix Asphalt Plant. In this investigation, a Batch Asphalt Plant was used to produce asphalt.

A. OVERVIEW OF THE PROCESS

After being stored in cold bins, unheated aggregates are weighed at cold-feed gates leading to a bucket elevator or conveyor. The aggregates are transported to the dryer, where they are dried using heat. The dryer’s exhaust is routed to an exhaust stack and dust collectors, where it is captured and processed. After being dried and heated, the aggregates are transferred via hot elevator to the screening unit, sorted by size and stored in hot bins (temporary storage). When needed, the heated bins release measured amounts into the weigh box. The aggregates and the required quantity of binder (bitumen) are then dumped into the pugmill. The asphalt is then transferred for delivery once it is ready. All of this can be seen in Fig. 4. The process-based categorization of the six WSs depicted in Fig. 5.

FIGURE 4: Flow diagram of asphalt plant showing fault at WS and DCS

\[
\begin{align*}
MP & = \{\text{Cold Feed System (CFS), Aggregate Dryer System (ADS),} \\
& \quad \text{Dust Control System (DCS), Hot Aggregate Screening (HAS),} \\
& \quad \text{Hot Bins System (HBS), Pugmill Mixing System (PMS),} \\
& \quad \text{Truck Loading System (TLS)}\} \\
\text{or,} \\
MP & = \{\text{CFS, ADS, DCS, HAS, HBS, PMS, TLS}\}
\end{align*}
\]

MP is a Null Matrix is the default setting. The procedure is carried out nonstop for one week. The system’s trip points are recorded. This set of trip points was established using the methods described by Yu et al. [26] and Han et al. [32]. Significant problems arise for the system in the workbench at tags:

\[
\begin{align*}
\text{CFS}(x_{14}), \text{ADS}(x_{22}), \text{DCS}(x_{31}), \text{HBS}(x_{42}), \text{PMS}(x_{24}) \\
M_P\alpha = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 1 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}
\end{align*}
\]
A one is recorded in the appropriate cell of the fault matrix whenever a trip point is reached. The procedure is supposed to terminate right now. After that, the Asphalt factory starts using the new method. The proposed method calculates the thresholds at which WSs will trip. Consequently, the system can decide whether the process will be finished or terminated immediately based on the dynamic assessment of its status thanks to this method.

\[
Thr(i) = \left( \sum_{k=i+\delta}^{i-\delta} (\Gamma - \delta)MPs(K) \right)
\]

CASE 1: The CFSUS (Cold Feed System Uncommanded Stop) bit is activated, as noted. An alarm is triggered when the Cold Feed System's proximity sensor becomes completely covered by dust. Once it detects an issue, it sends a signal to the main controller to halt operations. The CFS belt has a high chance of breaking due to the excessive weight on the conveyors, so this has been logged. If the system crashes, any pending aggregates in other WSs will immediately be moved to the reject pile. Specifically, the process has an MTTR of 20 minutes. These were the settings for the process's variables: \( \Gamma = 2, \delta = 1 \). Keep in mind that represents the total count of examined workstations before and after the WS disruption. Using MPs(K), we can see Ws's current status. For this reason, MPs(i+)=MPs(1)=1, while MPs(i-)=MPs(-1)=0 since there is no earlier station than WS1. To rewrite (5), we write: Thr(1)=((2-1)1+(2-1)0)=1
CASE 2: The DCSFVT (Dust Control System Fix Value Fault) bit is set in the ADS to indicate that a fault has occurred. WSs immediately before and after this one also operate normally; the batch is currently being processed in both. The ADS lies between the CFS and the DCS. As a result, the threshold value will depend on the data from both stations. Specifically, in this case, it can be determined by using the formula:

\[ M_{PS}(i + \delta) = M_{PS}(1) = 1 \]
\[ M_{PS}(i - \delta) = M_{PS}(-1) = 0 \]

where no station exists before WS1. Therefore, the threshold becomes

\[ Thr(2) = \left( \sum_{k=i+\delta}^{i-\delta} (\Gamma - \delta)M_{PS}(K) \right) = 2 \]  

There's a good chance that ADS will become out of whack with the conveyor turning the rotor. On the other hand, the batch is nearly finished, and to halt the process now would waste 30 tonnes of the processed batch.

CASE 3: An instance of DCSFF (Dust Control System Fluctuating Fault) is recorded whenever the flowmeter becomes jammed, leading to erroneous readings of the air that has been collected. Here, the threshold value (2) is added to the fixed ATP, keeping the system in its current state without halting the process until the batch is finished. Some aggregates will likely be lost, but there will be little financial impact if the entire batch is rejected. DCS is the only process that can't be halted mid-operation because its removal of superfluous dust from the aggregate has a negative impact on the batch. As a result, the threshold has a beneficial effect.

CASE 4: When the weight sensor provides a constant reading without providing context, this is known as an HBSFVF (Hot Bins System Fix Value Fault). Since the bitumen is weighed by the weight sensor, it plays a critical role in determining the final batch ratio. In order to keep the process running smoothly, the proposed method will use the secondary solution—namely, the time delay function—for the asphalt plant. The asphalt plant's calculations aren't perfect, but they're close enough to prevent the entire batch from being rejected. This threshold has a beneficial effect.

<table>
<thead>
<tr>
<th>Disruptive WS</th>
<th>Adjacent States</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFS</td>
<td>ADS</td>
<td>1</td>
</tr>
<tr>
<td>ADS</td>
<td>CFS</td>
<td>11</td>
</tr>
<tr>
<td>DCS</td>
<td>ADS</td>
<td>11</td>
</tr>
</tbody>
</table>

High cutoff values suggest restarting the process before terminating it. The DCSFVT alarm bit is the source of the DCS disruption. All threshold values are calculated with =1 and =2 in mind, and their relative weights are listed above (see Table 4). The fault's occurrence confirmed the activation of the trip points as predicted by Yu et al. [26]. Therefore, it came to a halt. The proposed method is superior because it allows for customizable trip point thresholds to meet the needs of different use cases.

\[ Alarm = 1 \text{ if } x(n) > x_tp + 1 \]  

\[ Alarm = 1 \text{ if } x(n) < x_tp + 1 \]  

B. FREQUENCY OF BEGINNINGS AND ENDS

Within the first week of operation, five significant incidents were reported. The breakpoints were determined concerning Yu and Wang [26]. Their system improves the trip point without involving any neighbouring WSs. Consequently, only two of the five major disruptions halted the process. However, the system can function normally in the other three scenarios. As can be seen in Fig. 6, the adopted method reduces the frequency of beginnings and endings. Having to start and stop less frequently by 60 percent is a notable achievement. However, by adjusting a few settings in the proposed algorithm, this figure can be varied widely. With =1, we conduct the analysis. However, depending on the method, it may increase to 2.

![Image of Figure 6: Reduction in number of start/stops](image)

C. DECREASED DOWNTIME

The MTTR value determines how long the process will be offline for maintenance. There are five distinct kinds of interruptions to the process. As was previously mentioned, this list is cut down to 3. The proposed method reduces downtime by an average of 60 minutes per week, as shown in Fig. 7, based on the MTTR value from the case study.
D. DROP IN REJECTION RATES, LETTER FORM,

As was mentioned earlier, the batch mixing asphalt plant in this case study has an hourly output of 1200 kg and a batch size of 600 kg (see Fig. 8). A savings of 600 kg of mixed aggregates can be realized by minimizing unnecessary starts and stops. The MTTR for this case study averages 20 minutes. The proposed method can save 60 minutes of downtime, directly affecting productivity and rejection by avoiding three out of every five stops.

![Comparison of the two Approaches](image)

FIGURE 7: Comparing the two methods' effects on reducing downtime

![Reduction in the value of rejection (in Kg)](image)

FIGURE 8: Reduction in the value of rejection (in Kg)

VI. CONCLUSION

This research suggests putting a number on how much one station's downtime affects its neighbours in a factory's production line. In terms of assigning threshold values based on the status of the process, the method is novel and more reliable. According to the data, the number of rejections, downtime, and starts/stops has drastically decreased. Compared to the presented method based on ATP, experimental results confirm the model. The proposed method reduces start-stop events by 60%, reducing rejections and downtime and ultimately improving consumer-centric value and efficiency. A more sophisticated and adaptable model for disruption handling in manufacturing processes could be attained in the future by including the workstation impact and tags weightage impact on threshold values.

FUNDING STATEMENT

The authors received no specific funding for this study.

CONFLICTS OF INTEREST

The authors declare there are no conflicts of interest to report regarding the present study.

REFERENCES

[17] L. A. Hadidi and A. Rahim, "Integrated models in production planning and
scheduling, maintenance and quality: A review Integrated models in production planning and scheduling, maintenance and quality: a review