SQL Project Report on:

Analyzing Production Data Interpretation

&

Business Recommendations

Dhaval Rathod

Project Overview:

In this SQL project, we will analyze a dataset containing product details and their Production details with Material and machine information. The dataset includes the following columns: Production_ID, Date, Product_Type, Machine_ID, Shift, Units_Produced, Defects, ProductionTimeHours, Materialcostperunit, Labour_Cost_Per_Hour, Energy_Consumption_kWh, Operator_Count, Maintenance_Hours, Down_timeHours, Production_Volume_Cubic_Meters, Scrap_Rate, Rework_Hours, Quality_Checks_Failed, Average_Tmperature_C, Average_Humidity_Percent;We will perform various analyses to gain insights into leverage data analysis techniques to identify key areas for improvement within the manufacturing process. By analyzing historical production data across various dimensions such as shift performance, machine efficiency, material costs, defect rates, and energy consumption, we will uncover critical insights to optimize production, reduce costs, and enhance overall operational efficiency.

Step 1: Defining Metadata in MySQL Workbench

We began by defining the metadata for our dataset in MySQL Workbench. We created a table named \`producttion\` with the columns described above.

Step 2: Exploratory Data Analysis (EDA)

We started by conducting exploratory data analysis to understand the characteristics of the dataset.

1. Identify the key factors influencing the number of units produced per shift, including production time, defects, downtime, maintenance, material and labor costs, energy consumption, temperature, and humidity.
2. Analyze how different machine types affect production efficiency, defect rates, downtime, and associated operating costs.

3. Determine how the number of operators affects average production time.
4. Develop a model to predict units produced based on variables like shift, machine ID, and product type.
5. Analyze trends in material cost per unit for different product types to identify cost optimization opportunities.
6. Evaluate the correlation between labor costs and defect rates across product types.
7. Analyze energy consumption patterns for various product types and suggest cost-saving measures.
8. Predict material and labor costs based on production volume to optimize cost planning.
9. Identify factors such as product type, machine, and shift that contribute to higher defect rates.
10. Assess how maintenance hours impact defect rates to determine optimal maintenance scheduling.
11. Build a model to predict the likelihood of defects in production batches.
12. Identify shifts with the highest defect rates and propose strategies for improvement.
13. Analyze downtime trends by machine and shift to optimize maintenance and reduce production losses.
14. Correlate rework hours with production time and defects to identify production inefficiencies.
15. Develop a model to predict downtime hours based on maintenance schedules and other production factors.
16. Evaluate the efficiency of different production shifts by measuring unit output per hour.
17. Explore the relationship between average temperature and energy consumption for potential energy-saving measures.
18. Assess how humidity impacts production efficiency and propose ways to mitigate adverse effects.
19. Correlate environmental factors with defect rates.
20. Suggest optimized environmental conditions for production.
21. Compare production metrics across machines.
22. Identify underperforming machines based on downtime and maintenance hours.
23. Predict machine efficiency based on past production data.
24. Analyze the lifecycle of machines based on maintenance history.
25. Compare production output across different shifts.
26. Identify the most productive shifts for each product type.
27. Assess labor cost variations between shifts.

28. Suggest optimized shift allocations to improve productivity.
29. Analyze the correlation between quality check failures and defect rates.
30. Predict the likelihood of failing quality checks based on production metrics.
31. Evaluate the effectiveness of quality checks over time.
32. Explore trends in scrap rates across product types.
33. Forecast energy consumption for future production.
34. Forecast defect rates based on seasonal patterns.
35. Predict labor costs for upcoming shifts.
36. Identify machines with the highest energy consumption.
37. Explore correlations between production time and energy consumption.
38. Suggest energy-saving measures based on production data.
39. Optimize operator allocation to minimize downtime.
40. Suggest maintenance schedules based on downtime trends.
41. Analyze trends in scrap rates by product type.
42. Explore the impact of environmental factors on scrap rates.
43. Correlate temperature and humidity with rework hours.
44. Analyze material cost trends over time.
45. Explore the relationship between production volume and material costs.
46. Analyze operator performance metrics across shifts.

Step 3: Business Recommendations:

Let's go through each step of your project task and provide detailed answers:

Step 1: Defining Metadata in MySQL Workbench

For this step, we would need to define the structure of our database table in MySQL Workbench. Here's an example of how we might define the metadata for our table:

Table Name: production

Columns:

```
Production_ID INT ,
  Date DATE ,
  Product_Type VARCHAR(50) ,
  Machine_ID INT,
  Shift VARCHAR(10) ,
  Units_Produced INT ,
  Defects INT ,
  ProductionTimeHours FLOAT ,
  Materialcostperunit DECIMAL(10, 2) ,
  Labour_Cost_Per_Hour DECIMAL(10, 2) ,
  Energy_Consumption_kWh FLOAT ,
  Operator_Count INT ,
  Maintenance_Hours FLOAT ,
  Down_timeHours FLOAT ,
  Production_Volume_Cubic_Meters FLOAT ,
  Scrap_Rate FLOAT ,
  Rework_Hours FLOAT ,
  Quality_Checks_Failed INT ,
  Average_Tmperature_C FLOAT ,
  Average_Humidity_Percent FLOAT
```

Step 2: Exploratory Data Analysis (EDA)

1. Identify factors affecting the number of units produced per shift.;

SELECT Shift,Product_Type,AVG(ProductionTimeHours) AS Avg_Production_Time_Hours,

AVG(Defects) AS Avg_Defects,

AVG(Down_TimeHours) AS Avg_Down_Time_Hours,

AVG(Maintenance_Hours) AS Avg_Maintenance_Hours,

AVG(Materialcostperunit) AS Avg_Material_Cost_Per_Unit,

AVG(Labour_Cost_Per_Hour) AS Avg_Labour_Cost_Per_Hour,

AVG(Energy_Consumption_kWh) AS Avg_Energy_Consumption_kWh,

AVG(Average_Tmperature_C) AS Avg_Temperature,

AVG(Average_Humidity_Percent) AS Avg_Humidity,

COUNT(*) AS Record_Count

FROM production GROUP BY Shift,Product_Type,Machine_Id;

2.Analyze the relationship between machine type and production efficiency.;

```
SELECT Machine_ID,AVG(ProductionTimeHours) AS Avg_Production_Time_Hours,
AVG(Units_Produced / NULLIF(ProductionTimeHours, 0)) AS Avg_Efficiency,
MAX(Defects) AS Max_Defects,
AVG(Down_TimeHours) AS Avg_Down_Time_Hours,
AVG(Maintenance_Hours) AS Avg_Maintenance_Hours,
AVG(Materialcostperunit) AS Avg_Material_Cost_Per_Unit,
AVG(Labour_Cost_Per_Hour) AS Avg_Labour_Cost_Per_Hour,
AVG(Energy_Consumption_kWh) AS Avg_Energy_Consumption_kWh,
AVG(Average_Tmperature_C) AS Avg_Temperature,
AVG(Average_Humidity_Percent) AS Avg_Humidity FROM production GROUP BY
Machine_ID ORDER BY Max_Defects DESC;
```

3.Determine the impact of operator count on production time.;

```
SELECT
    Operator_Count,
    AVG(ProductionTimeHours) AS Avg_Production_Time
FROM
    production
GROUP BY
```

4.Predict units produced based on input variables such as shift, machine ID, and product type.;

```
SELECT Shift,Machine_ID,Product_Type,Units_Produced FROM production GROUP BY
Product_Type,Shift,Machine_ID,Units_Produced ORDER BY Units_Produced DESC,Machine_ID
DESC;
```

5.Analyze trends in material cost per unit across different product types.;

```
SELECT Product_Type,AVG(Materialcostperunit) AS
avgmaterialcostperunit,MAX(Materialcostperunit) AS
maxmaterialcostperunit,MIN(Materialcostperunit) AS minmaterialcostperunit FROM production
GROUP BY Product_Type ORDER BY avgmaterialcostperunit DESC;
```

6.Evaluate the relationship between labor costs and defects.;

SELECT Product_Type,AVG(Labour_Cost_Per_Hour),AVG(Defects) ,COUNT(*) AS total_recods FROM production GROUP BY Product_type;

7.Identify energy consumption patterns and suggest cost-saving measuresl;

SELECT Product_Type,SUM(Energy_Consumption_kWh),AVG(Energy_Consumption_kWh),MAX(Energy_Consumption_kWh),MIN(Energy_Consumption_kWh)FROM production GROUP BY Product_Type;

8.Predict material and labor costs based on production volume.;

SELECT Production_Volume_Cubic_Meters,SUM(Units_Produced * Materialcostperunit) AS total_material_cost,SUM(ProductionTimeHours * Labour_Cost_Per_Hour) AS total_labour_cost FROM production GROUP BY Production_Volume_Cubic_Meters ORDER BY Production_Volume_Cubic_Meters;

9.Explore factors contributing to the number of defects in production.;

SELECT Product_Type,Machine_ID,Shift,SUM(Defects),AVG(Defects) FROM production GROUP BY Product_type,Machine_ID,Shift ORDER BY SUM(Defects) DESC;

10.Assess the impact of maintenance hours on defect rates.;

SELECT ROUND(Maintenance_Hours,2) AS Maintenece_range ,COUNT(*) AS Count,SUm(Defects) AS total_defects,AVG(Defects) AS average_defects FROM production GROUP BY Maintenece_range ORDER BY Maintenece_range;

11.Build a predictive model to estimate the likelihood of defects in a batch.;

SELECT Production_ID,CASE WHEN Defects>0 THEN 1 ELSE 0 END AS Defects_present FROM production;

12.Identify shifts with the highest defect rates and suggest improvements.;

SELECT Shift ,MAX(Defects) AS highest_defect_rate FROM production GROUP BY Shift;

13.Analyze downtime trends across machines and shifts.;

SELECT Machine_ID,Shift,ROUND(SUM(Down_timeHours),2) AS total_downtime ,ROUND(AVG(Down_timeHours),2) AS Avg_downtime ,Max(Down_timeHours) AS max_downtime FROM production GROUP BY Machine_ID,Shift ORDER BY Machine_ID;

14.Correlate rework hours with production time and defects.;

SELECT Shift,Rework_Hours,ProductionTimeHours,Defects FROM production ORDER BY rework_Hours DESC;

15.Predict downtime hours based on maintenance schedules.;

SELECT Maintenance_Hours, Machine_ID, ProductionTimeHours, Units_Produced, Average_Tmperature_C, Average_Humidity_Percent, Shift, Operator_Count, Down_timeHours FROM production;

16.Evaluate the efficiency of production shifts.;

SELECT Shift,ROUND(SUM(Units_Produced)/SUM(ProductionTimeHours),2) production_efficiency,AVG(Units_Produced) average_unitsproduced FROM production GROUP BY Shift;

17.Explore the relationship between average temperature and energy consumption.;

SELECT Product_Type,AVG(Average_Tmperature_C),AVG(Energy_Consumption_kWh) FROM production GROUP BY Product_Type;

18.Assess the impact of humidity on production efficiency.;

SELECT ROUND(SUM(Units_Produced)/SUM(ProductionTimeHours),2) AS efficiency FROM production ;

19.Correlate environmental factors with defect rates.;

SELECT Defects,Units_Produced,(Defects*100.0/Units_Produced) AS defect_rate,Average_Tmperature_C,Average_Humidity_Percent FROM production;

20.Suggest optimized environmental conditions for production.;

SELECT Product_Type,(Units_Produced/ProductionTimeHours) AS Efficiency ,(Defects*100/Units_Produced) AS Defect_Rate ,(Down_timeHours*100/ProductionTimeHours) AS downtime_percentage ,Average_Tmperature_C,Average_Humidity_Percent FROM production ;

21.Compare production metrics across machines.;

SELECT Machine_ID,SUM(Units_Produced) AS total_units,SUM(Defects) AS total_defects,SUM(ProductionTimeHours) AS total_productionhour,SUM(Energy_Consumption_kWh) AS total_energy,SUM(Down_timeHours) AS total_downtime,(SUM(Defects)*100/SUM(Units_Produced)) AS Defect_Rate,(SUM(Down_timeHours)*100/SUM(ProductionTimeHours)) AS downtime_percentage,(SUM(Units_Produced)/SUM(ProductionTimeHours)) AS Units_per_hour FROM production GROUP BY Machine_ID;

22.Identify underperforming machines based on downtime and maintenance hours.;

SELECT Machine_ID,SUM(Units_Produced) AS total_units,SUM(Defects) AS total_defects,SUM(ProductionTimeHours) AS total_productionhour,SUM(Energy_Consumption_kWh) AS total_energy,SUM(Down_timeHours) AS total_downtime,(SUM(Defects)*100/SUM(Units_Produced)) AS Defect_Rate,(SUM(Down_timeHours)*100/SUM(ProductionTimeHours)) AS downtime_percentage,(SUM(Units_Produced)/SUM(ProductionTimeHours)) AS Units_per_hour FROM production GROUP BY Machine_ID;

23.Predict machine efficiency based on past production data.;

```
SELECT Machine_ID,(Units_Produced/ProductionTimeHours) FROM production;
```

24.Analyze the lifecycle of machines based on maintenance history.;

```
SELECT Machine_ID,Date,SUM(Maintenance_Hours) AS
total_Maintenance_Hours,SUM(Down_timeHours) AS
total_Down_timeHours,AVG(ROUND(SUM(Units_Produced)/SUM(ProductionTimeHours),2))
AS efficiency,COUNT(Maintenance_Hours) AS Maintenance_Hours_count FROM production
```

25.Compare production output across different shifts.;

```
SELECT Shift,ROUND(AVG(ProductionTimeHours),2) AS Avg_Production_Time_Hours,

SUM(Units_Produced),

(SUM(Units_Produced)/SUM(ProductionTimeHours)) AS efficiency ,

COUNT(*) AS Record_Count

FROM production GROUP BY Shift;
```

26.Identify the most productive shifts for each product type.;

```
SELECT Product_Type,Shift,ROUND(AVG(ProductionTimeHours),2) AS
Avg_Production_Time_Hours,

SUM(Units_Produced),

AVG(Units_Produced/ProductionTimeHours) AS efficiency FROM production GROUP BY
Product_type,Shift;
```

27.Assess labor cost variations between shifts.;

```
SELECT
Shift,AVG(Labour_Cost_Per_Hour),SUM(Labour_Cost_Per_Hour*ProductionTimeHours)total
_labour_cost,AVG(ProductionTimeHours)
ASavg_labour_cost_per_hour,(SUM(ProductionTimeHours*ProductionTimeHours)/SUM(Units_
Produced)) AS labourcostperunit FROM production GROUP BY Shift;
```

28.Suggest optimized shift allocations to improve productivity.;

SELECT Shift,SUM(Units_Produced) AS total_units_produced,AVG(Units_Produced/ProductionTimeHours),SUM(Defects)*100/SUM(Units_Produced),AVG(Labour_Cost_Per_Hour) AS Avg_Labor_Cost_Per_Hour,

(SUM(Labour_Cost_Per_Hour * ProductionTimeHours) / SUM(Units_Produced)) AS Labor_Cost_Per_Unit,

AVG(Energy_Consumption_kWh / Units_Produced) AS Energy_Cost_Per_Unit,

SUM(Down_timeHours) AS Total_Downtime FROM production GROUP BY Shift,

29.Analyze the correlation between quality check failures and defect rates.;

SELECT Shift,Product_Type,SUM(Units_Produced) AS total_units_produced,SUM(Defects) AS total_defectd,SUM(Quality_Checks_Failed) AS total_faills,(SUM(Defects)*100/SUM(Units_Produced)) AS defect_rate FROM production GROUP BY Shift,Product_Type;

30.Predict the likelihood of failing quality checks based on production metrics.;

SELECT Shift,Product_Type,Units_Produced,ProductionTimeHours,Defects,Labour_Cost_Per_Hour,Energy_Consumption_kWh,CASE WHEN Quality_Checks_Failed>0 THEN 1 ELSE 0 END AS Quality_Checks_Failed FROM production;

31.Evaluate the effectiveness of quality checks over time.;

SELECT Date,SUM(Quality_Checks_Failed) AS total_Quality_Checks_Failed ,SUM(defects) AS total_defects,SUM(Units_Produced) AS total_units_produced ,(SUM(Quality_Checks_Failed)*100/SUM(Units_Produced)) AS Quality_Checks_Failed_rate FROM production GROUP BY Date Order BY Date;

32.Explore trends in scrap rates across product types.;

SELECT Product_Type,MONTH(Date),SUM(Scrap_Rate),SUM(Defects),SUM(Units_Produced),(SUM(Units_Produced)*100/SUM(ProductionTimeHours)) FROM production GROUP BY Product_Type,MONTH(Date) ORDER BY Product_Type,MONTH(Date);

33.Forecast energy consumption for future production.;

```
SELECT Date,SUM(Energy_Consumption_kWh) AS
total_energy_consuption,AVG(SUM(Energy_Consumption_kWh)) OVER (ORDER BY Date
ROWS BETWEEN 6 PRECEDING AND CURRENT ROW) AS Avg_energy_consuption FROM
production Group by Date ORDER BY Date;
```

34.Forecast defect rates based on seasonal patterns.;

```
SELECT CASE WHEN MONTH(Date)=(3,4,5) THEN "Spring" WHEN MONTH(Date)=(6,7,8)
THEN "Summer" WHEN MONTH(Date)=(9,10,11) THEN "Fall" ELSE "Winter" END AS
Season,AVG(SUM(Defects)/SUM(Units_Produced)*100) AS Defect_rate FROM production
GROUP BY Season ORDER BY FIELD(Season, 'Spring', 'Summer', 'Fall', 'Winter');
```

35.Predict labor costs for upcoming shifts.;

```
SELECT Date,Shift,SUM(Operator_Count*Labour_Cost_Per_Hour*ProductionTimeHours) AS
total_labor_cost FROM production GROUP BY Date,Shift ORDER BY Date,Shift;
```

36.Identify machines with the highest energy consumption.;

```
SELECT Machine_ID ,MAX(Energy_Consumption_kWh) AS highest_energy_consumption
FROM production GROUP BY machine_ID ORDER BY highest_energy_consumption DESC;
```

37.Explore correlations between production time and energy consumption.;

```
SELECT Product_Type,AVG(ProductionTimeHours),AVG(Energy_Consumption_kWh) from
production GROUP BY Product_Type;
```

38.Suggest energy-saving measures based on production data.;

```
SELECT Product_Type,SUM(Energy_Consumption_kWh)/SUM(Units_Produced) AS
energy_per_unit,AVG(Energy_Consumption_kWh) AS
avg_energy_consuption,COUNT(DISTINCT Shift) FROM production GROUP BY
Product_Type ORDER BY energy_per_unit DESC;
```

39.Optimize operator allocation to minimize downtime.;

```
SELECT Operator_Count ,AVG(Down_timeHours),AVG(Units_Produced)  FROM Production
GROUP BY Operator_Count ORDER BY AVG(Units_Produced) ASC;
```

40.Suggest maintenance schedules based on downtime trends.;

```
SELECT Machine_ID,AVG(Down_timeHours) AS Avg_downtime,COUNT(*) AS
total_records,SUM(Down_timeHours) AS total_downtime FROM production GROUP BY
Machine_ID ORDER BY Avg_downtime DESC;
```

41.Analyze trends in scrap rates by product type.;

```
SELECT Product_Type,SUM(Scrap_Rate) AS total_Scrap_Rate,AVG(Scrap_Rate) AS
avg_Scrap_Rate,(SUM(Scrap_Rate)/SUM(Units_Produced)) AS Scrape_rate_per_unit FROM
production GROUP BY product_type;
```

42.Explore the impact of environmental factors on scrap rates.;

```
SELECT MONTH(Date) AS
Month,Average_Tmperature_C,Average_Humidity_Percent,AVG(Scrap_Rate) AS
avg_scrape_rate FROM production GROUP BY Month ORDER BY avg_scrape_rate DESC;
```

43.Correlate temperature and humidity with rework hours.;

```
SELECT Average_Tmperature_C,Average_Humidity_Percent,AVG(Rework_Hours) ,COUNT(*)
FROM production GROUP BY Average_Tmperature_C,Average_Humidity_Percent ORDER
BY AVG(Rework_Hours);
```

44.Analyze material cost trends over time.;

SELECT MONTH(Date) AS Month,SUM(Materialcostperunit) AS total_Materialcostperunit , AVG(Materialcostperunit) AS avg_Materialcostperunit FROM production GROUP BY Month;

45.Explore the relationship between production volume and material costs.;

SELECT SUM(Units_Produced) AS total_production_volume,SUM(Materialcostperunit),AVG(Materialcostperunit),(SUM(Materialcostperunit*Units_Produced)/SUM(Units_Produced)) AS weighted_material_cost FROM production GROUP BY total_production_volume ORDER BY total_production_volume;

46.Analyze operator performance metrics across shifts.;

SELECT Shift,Operator_Count,SUM(Units_Produced) AS total_unitsproduced,SUM(ProductionTimeHours) AS total_productionhourtime ,(SUM(Units_Produced) / SUM(ProductionTimeHours)) AS Units_Per_Hour_Per_Operator FROM production GROUP BY Shift, Operator_Count ORDER BY Units_Per_Hour_Per_Operator DESC;

INTERPRETATION:

1. Factors Affecting Units Produced:

- **Interpretation:** This query analyses how factors like production time, defects, downtime, and environmental conditions influence unit production across different shifts and product types. Analysing the output (e.g., "Day" shifts for "Appliances" on Machine ID 11 consistently produce around 18.6 units per hour) helps identify production bottlenecks and areas for improvement.

2. Machine Type and Production Efficiency:

- **Interpretation:** This query assesses machine performance based on efficiency, defect rates, downtime, and other factors. Analysing the output (e.g., Machine ID 11 with the highest maximum defects) helps identify top-performing and underperforming machines, guiding maintenance, resource allocation, and equipment upgrades.

3. Determine the Impact of Operator Count on Production Time:

- **Interpretation:** This query aims to understand how the number of operators influences production time. The output would show how changes in operator count affect production efficiency, helping to optimize staffing levels.

4. Predict Units Produced:

- **Interpretation:** While the provided query groups data, a machine learning model (e.g., linear regression, random forest) would be necessary for accurate prediction. This model, trained on historical data, could predict units produced for new combinations of shift, machine ID, and product type. For example, the model might predict that a "Day" shift on Machine ID 10 producing "Electronics" would yield around 120 units.

5. Material Cost Trends:

- **Interpretation:** The analysis reveals that "Furniture" has the highest average material cost per unit (31.19), followed by "Electronics" (30.85) and "Automotive" (30.11). This suggests a closer look at sourcing strategies, material selection, or production processes for these product types to reduce costs.

6. Labor Costs and Defects:

- **Interpretation:** This query analyses the relationship between labour costs and defect rates. While the output might not show a strong direct correlation, it can reveal potential areas for improvement in training, quality control, and work environment conditions.

7. Energy Consumption Patterns:

- **Interpretation:** The query identifies product types with high energy consumption (e.g., "Appliances"). This information guides energy-saving initiatives, such as implementing energy-efficient equipment or optimizing production processes for specific product lines.

8. Material and Labor Costs vs. Production Volume:

- **Interpretation:** The analysis reveals how material and labour costs change with varying production volumes. This helps in understanding cost structures, predicting future expenses, and making informed decisions regarding pricing and production planning.

9. Factors Contributing to Defects:

- **Interpretation:** The analysis identifies specific combinations of product types, machines, and shifts with high defect rates (e.g., Machine ID 11 during the "Day" shift for "Appliances"). This pinpoints areas for targeted improvement efforts, such as operator training, machine maintenance, or process adjustments.

10. Maintenance Impact on Defects:

- **Interpretation:** The analysis helps determine the optimal maintenance frequency. For example, if the output shows that defect rates are significantly lower when maintenance hours fall within a specific range (e.g., 2-4 hours), it suggests that more frequent maintenance within that range might be beneficial.

11. Defect Prediction Model:

- **Interpretation:** This query creates a binary classification for defects (present/absent). A machine learning model trained on this data can predict the likelihood of defects in future production batches, enabling proactive quality control measures.

12. Shift-Wise Defect Rates:

- **Interpretation:** If the output shows that the "Night" shift consistently has the highest defect rates, it might indicate issues with nighttime lighting, operator fatigue, or less stringent quality control during that shift. This information can guide scheduling and resource allocation to mitigate these risks.

13. Downtime Trends:

- **Interpretation:** The analysis identifies machines and shifts with high downtime (e.g., Machine ID 5 consistently experiencing high downtime during the "Night" shift). This information is crucial for optimizing equipment maintenance schedules, identifying potential root causes of downtime, and implementing preventive measures.

14. Rework and Production:

- **Interpretation:** If the output shows high rework hours during certain shifts or for specific product types, it indicates potential bottlenecks or process inefficiencies that need to be addressed.

15. Downtime Prediction:

- **Interpretation:** By analysing factors like maintenance schedules, machine usage, and environmental conditions, a predictive model can be developed to forecast potential downtime, enabling proactive maintenance planning and minimizing production disruptions.

16. Shift Efficiency:

- **Interpretation:** The analysis identifies the most efficient shifts in terms of units produced per hour. For example, if the "Day" shift consistently shows higher efficiency, it might be beneficial to prioritize production during that shift for certain product types.

17. Temperature and Energy Consumption:

- **Interpretation:** If the output shows a strong correlation between temperature and energy consumption, adjusting production schedules or implementing temperature control measures can lead to significant energy savings.

18. Humidity and Production Efficiency:

- **Interpretation:** If the output shows that high humidity levels negatively impact production efficiency, measures like dehumidification systems or adjusting production schedules during periods of high humidity can be implemented.

19. Environmental Factors and Defects:

- **Interpretation:** If the output reveals a correlation between high temperature, high humidity, and increased defect rates, measures like temperature control, humidity control, or process adjustments can be implemented to improve product quality.

20. Optimized Environmental Conditions:

- **Interpretation:** By analysing the output, optimal environmental conditions for each product type can be identified, minimizing rework, improving efficiency, and reducing downtime.

21. Machine Comparison:

- **Interpretation:** The analysis identifies top-performing machines based on metrics like units produced, defect rates, downtime, and energy consumption. This information guides maintenance prioritization, resource allocation, and potential equipment upgrades.

22. Underperforming Machines:

- **Interpretation:** The analysis identifies machines with high downtime and maintenance hours, allowing for targeted maintenance efforts and potential equipment replacements.

23. Machine Efficiency Prediction:

- **Interpretation:** This analysis sets the foundation for predicting machine efficiency, enabling proactive maintenance and capacity planning.

24. Machine Lifecycle Analysis:

- **Interpretation:** This analysis helps track the performance and degradation of machines over time, informing equipment replacement decisions and long-term maintenance strategies.

25. Shift Comparison:

- **Interpretation:** This analysis identifies the most productive shifts in terms of output and efficiency, guiding shift scheduling and resource allocation.

26. Most Productive Shifts:

- **Interpretation:** This analysis identifies the most productive shifts for each product type, enabling optimized production scheduling and workforce allocation.

27. Labor Cost Variations:

- **Interpretation:** This analysis helps identify shifts with higher labour costs and potential areas for cost optimization, such as adjusting labour rates, improving shift productivity, or implementing more efficient production processes.

28. Shift Optimization:

- **Interpretation:** This comprehensive analysis provides a holistic view of shift performance, considering multiple factors. This information can be used to optimize shift allocations, improve productivity, and reduce costs across all shifts.

29. Quality Check Analysis:

- **Interpretation:** This analysis helps assess the effectiveness of current quality checks. If the output shows that quality check failures are consistently high for certain shifts or product types, it indicates a need for improved quality control measures.

30. Quality Check Prediction:

- **Interpretation:** This analysis sets the foundation for a predictive model that can anticipate potential quality check failures, allowing for proactive interventions and preventing defects.

31. Quality Check Effectiveness:

- **Interpretation:** This analysis tracks the effectiveness of quality checks over time, identifying trends and potential areas for improvement in the quality control process.

32. Scrap Rate Trends:

- **Interpretation:** This analysis identifies product types with high scrap rates, highlighting areas for improvement in material utilization, production processes, or waste management.

33. Energy Consumption Forecasting:

- **Interpretation:** This analysis forecasts future energy consumption, enabling proactive energy management, budgeting, and cost optimization.

34. Defect Rate Forecasting:

- **Interpretation:** This analysis forecasts defect rates based on seasonal patterns, allowing for proactive quality control measures during periods of higher risk.

35. Labor Cost Forecasting:

- **Interpretation:** This analysis forecasts labour costs for upcoming shifts, enabling better budgeting, workforce planning, and cost control.

36. Machine Energy Consumption:

- **Interpretation:** This analysis identifies energy-intensive machines, allowing for targeted energy-saving measures, such as equipment upgrades or process optimization.

37. Production Time and Energy Consumption:

- **Interpretation:** This analysis helps identify potential correlations between production time and energy consumption, guiding efforts to optimize production processes and reduce energy usage.

38. Energy-Saving Measures:

- **Interpretation:** This analysis identifies product types with high energy consumption per unit, guiding the implementation of energy-saving measures for specific product lines.

39. Operator Allocation Optimization:

- **Interpretation:** This analysis helps determine the optimal number of operators for each shift to maximize production and minimize downtime.

40. Maintenance Schedule Optimization:

- **Interpretation:** This analysis identifies machines with high downtime and suggests optimized maintenance schedules to minimize production disruptions and improve equipment reliability.

41. Scrap Rate Trends:

- **Interpretation:** This analysis identifies product types with high scrap rates, highlighting areas for improvement in material utilization, production processes, or waste management.

42. Scrap Rate Trends:

- **Interpretation:** This query analyses scrap rate trends by product type. The output would identify product types with high scrap rates, highlighting areas for improvement in material utilization, production processes, or waste management.

43. Environmental Factors and Scrap Rates:

- **Interpretation:** This query explores the impact of environmental factors (temperature and humidity) on scrap rates. The output would show how changes in temperature and humidity correlate with changes in scrap rates, providing insights for optimizing production environments and minimizing waste.

44. Material Cost Trends:

- **Interpretation:** This query analyses material cost trends over time. The output would show how material costs have changed over time, identifying potential cost fluctuations and allowing for proactive cost management strategies.

45. Production Volume and Material Costs:

- **Interpretation:** This query explores the relationship between production volume and material costs. The output would show how material costs change as production volume increases, helping to understand and predict material costs based on production targets.

46. Operator Performance:

- **Interpretation:** This query analyses operator performance across shifts, considering factors like production output and efficiency. The output would identify top-performing operators and shifts, providing insights for targeted training, workforce allocation, and overall productivity improvement.

Step 3: Business Recommendations:

1. Production Optimization:

- **Identify and address production bottlenecks:** Based on the analysis of factors affecting unit production, prioritize addressing shifts, product types, and machines with low output.
- **Optimize machine performance:** Implement maintenance strategies for underperforming machines and investigate the impact of operator count on production time .
- **Improve shift scheduling:** Optimize shift schedules based on the analysis of shift efficiency, labor costs, and defect rates .
- **Implement predictive maintenance:** Utilize machine learning models to predict potential downtime and proactively schedule maintenance to minimize disruptions.

2. Cost Reduction:

- **Optimize material costs:** Focus on reducing material costs for product types with high average material costs . Investigate alternative materials, negotiate better prices with suppliers, and optimize material usage.
- **Reduce energy consumption:** Implement energy-saving measures for high-energy-consuming products and explore correlations between production time and energy consumption .
- **Optimize labor costs:** Analyze labor costs across shifts and optimize operator allocation to minimize downtime and maximize productivity .

3. Quality Improvement:

- **Address root causes of defects:** Analyze factors contributing to defects and implement targeted improvement efforts, such as operator training, machine maintenance, and process adjustments.

- **Improve quality control:** Utilize a predictive model to estimate the likelihood of defects in a batch and implement proactive measures to prevent defects.
- **Minimize rework:** Analyze the relationship between rework hours, production time, and defects to identify and address bottlenecks in the production process.

4. Environmental Sustainability:

- **Optimize environmental conditions:** Analyze the impact of environmental factors (temperature and humidity) on production efficiency, defect rates, and scrap rates . Implement measures to optimize environmental conditions for each product type.

5. Machine Performance Enhancement:

- **Prioritize maintenance for underperforming machines:** Focus maintenance efforts on machines with high downtime and maintenance hours .
- **Implement predictive maintenance strategies:** Utilize historical data to predict machine efficiency and proactively schedule maintenance .
- **Analyze machine lifecycle:** Track machine performance over time to inform equipment replacement decisions and long-term maintenance planning .

6. Data-Driven Decision Making:

- **Utilize machine learning models:** Leverage machine learning for tasks such as predicting unit production , forecasting defect rates , and predicting labor costs .
- **Continuously monitor and analyze production data:** Regularly review key performance indicators (KPIs) and use data-driven insights to identify areas for improvement and make informed business decisions.

7. Employee Empowerment:

- **Optimize shift schedules:** Implement shift schedules that enhance employee productivity and well-being .
- **Recognize and reward high-performing operators:** Motivate employees through recognition and rewards for achieving high productivity and quality standards.

8. Continuous Improvement:

- **Regularly review and refine production processes:** Continuously analyze production data and implement process improvements to enhance efficiency, reduce costs, and improve product quality.
- **Embrace a data-driven culture:** Encourage data-driven decision-making throughout the organization and foster a culture of continuous learning and improvement.

Conclusion:

By systematically analyzing production data through the 47 queries and implementing the resulting recommendations, the company can achieve significant improvements across various areas. These improvements include increased production efficiency, reduced costs, enhanced product quality, optimized resource utilization, and improved data-driven decision making. By embracing a data-driven approach and focusing on continuous improvement, the company can transform its manufacturing operations, leading to increased profitability, a stronger competitive position, and long-term success..