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Implementation of Production Planning and Scheduling - A Data Mining Approach

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Abstract: ***According to experience, raw material management is a major operational difficulty in the business. The importance of raw materials to the efficient operation of a manufacturing organization cannot be emphasized; the right quality and quantity are critical. Planning and production include determining the level of activity, turn - over, and final profit in a corporation, as well as minimum and maximum stock levels. Raw material management in a manufacturing organization requires specific care and scrutiny in order to achieve uninterrupted production cycles and better operational performance. Maintaining an acceptable stock level can also enhance the amount of available operating capital that can be put to better use. Material management is defined as the coordination of efforts (planning, managing, organizing, and directing) aimed at achieving efficiency in a manufacturing organization's procurement, transportation, stocking, and utilization of inputs. The effectiveness and efficiency of material management have a direct impact on the organization's overall success. This study provides a literature review on data mining definitions as well as a categorization of existing techniques to using data mining to manage production complexity in order to assist manufacturing organizations in implementing data mining.***

Keywords: Data Mining, Hierarchical Clustering Algorithm and Association Rule

1. Introduction

For translating data into meaningful knowledge, data mining is a natural answer. For a variety of applications, the retrieved knowledge can be utilized to model, classify, and make predictions. The essential data for analysis can be obtained during the normal operation of the manufacturing process being researched, which is a primary benefit of data mining over conventional experimental techniques.

As a result, it is rarely essential to dedicate machines or processes just to data collection. Data mining (DM) and knowledge discovery in databases (KDD) have become critical methods for achieving the goal of intelligent and automated data analysis. Data mining is a step in the KDD process that entails using specific algorithms to extract patterns (models) from large amounts of data.

Data mining has been used in a variety of industrial and logistics fields over the years, but only to a limited extent.

This research focuses on the use of data mining techniques or algorithms to the manufacturing business, namely in the areas of stock management and delivery. The Hierarchical Clustering Algorithm and Association Rule are Data Mining Algorithms/Functions that can be used for Production planning and scheduling. This study looks at how data mining techniques or algorithms can be applied to the manufacturing business, namely stock management and delivery.

2. Methodology

Figure 1 presents the process for implementation of the system. Each of these steps is described further

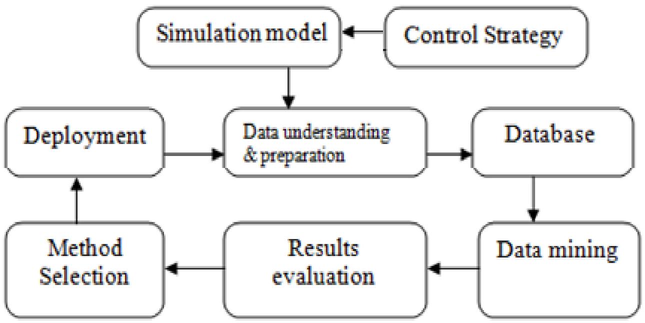

Figure 1: System Implementation Procedure

- ***Strategy for Control***

The simulation control strategy is supposed to help the production meet specified objectives.

To improve Metrics, the focused KPIs in this case study are measured in a short period of time and comprise total finished products, under production products, and stock control. These indicators have a significant impact on the observed process and have a favorable impact on the observed process' performance. All of these essential indicators are simultaneously monitored for fulfillment.

To achieve production efficiency and meet the desired production goals, the input production parameters must be changed accordingly. The control plan's goals are developed using a model that describes the complicated relationships between various sets of input constraints.

Further assessment of the objectives and standards of the production process was made, based on the separate

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production objectives and their quantitative characteristics. The total goals it should be achieving are more than 600 finished products. This variable maybe right or wrong, as depicted in Figure 2.

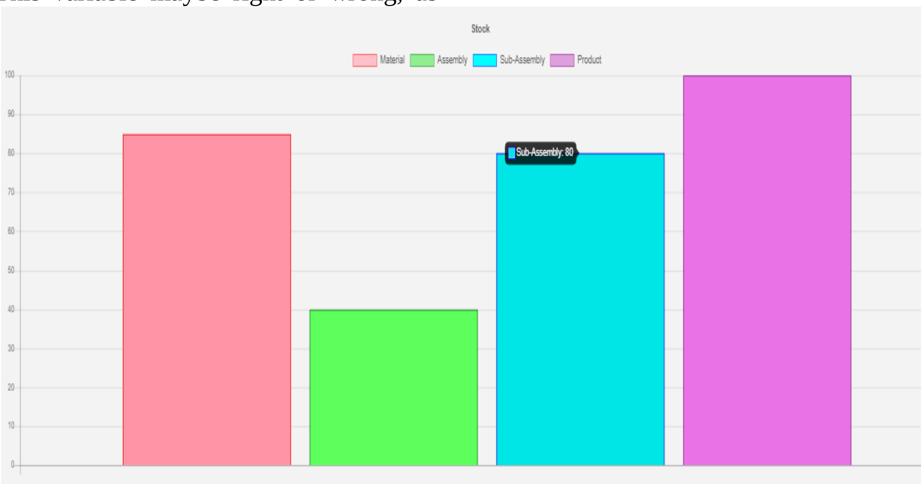


Figure 2 (a): Predicted Data (Inventory Management)

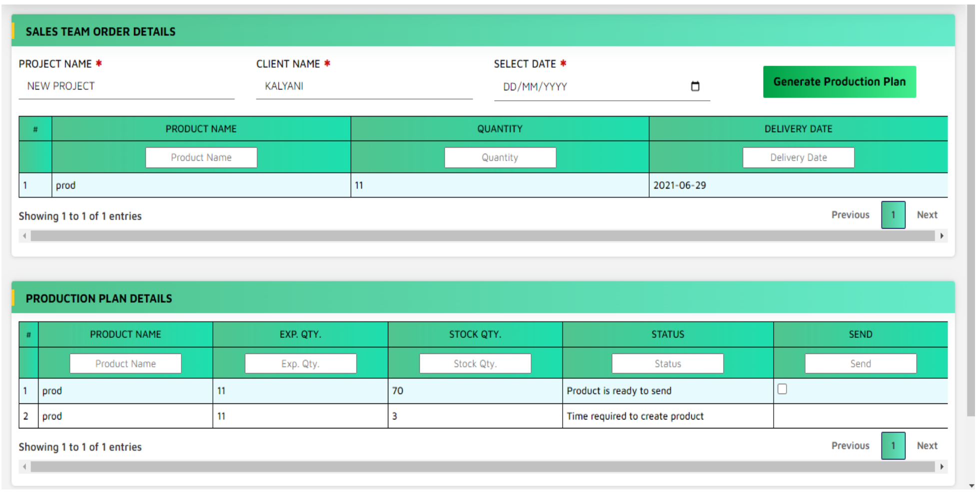


Figure 2 (b): Predicted Data (Production Plan)

If the Total Goals variable matches realtime data, we can conclude that the process is achieving all of the objectives. If No, yet none of the objectives are accomplished at the same time.

- ***Simulation Model***

This designed and built a prototype or simulation to create production data depending on stock. In addition, this simulated model was used to control the supply of Production goods. The simulation model was built using simulation principles from different events, and the production system model was established. The input data was taken from the current state of the manufacturing process. This includes product names, assembly and sub - assembly names, as well as raw material items and the sizes into which they should be cut. Entities in the discrete event simulation model dictated all of these different output parameters. If the aforementioned event occurs and the technical activity is completed, this model aids in the calculation of KRIs and KPIs. To validate the simulation model, the real system is used as a benchmark. The validation procedure involves much iteration to compare the simulation to the behavior and outcomes of the real system. After calibrating the simulation, an exact model of the actual unit is obtained. For the sake of the next step of the analysis, it is treated as a closed unit, with its shape remaining unchanged.

- ***Database***

The values reached by the chosen parameters of the goals and the control parameters' input variables while monitoring the production system are represented by the data gathered in the various runs of the simulation models. The time intermission for each model run was set to a month. Mysql 5.7.33 was chosen as the database for storing the process data.

- ***Methodology Used***

As shown in figure 1, the methodology used for this analysis was Divisive Clustering Algorithm and Association Rule Mining. The first mentioned clustering algorithm necessitates a method for breaking a cluster that contains all of the data and then recursively splitting clusters until all of the data has been split into singletons. And the later, finds interesting associations and relationships among large sets of data items. This rule shows how frequently an item set occurs in a transaction. The output from these methods is segregation of data for stock control and details of production plan for delivery to customers based on priority set by Production Team. An implementation of a fresh batch of input framework was done to verify the predicted values. For the progression of discovering information from databases, this data was used for input. The goal was the comparison of predicted and simulated values and simultaneously determining if the models selected and algorithms specified are usable for making decisions to control the process. This evaluation is described in the results.

- ***Methods of Mining Data***

We require cognition strategies and approaches to correctly apply the solved problem of prediction. Based on the authors' decision to execute prediction through the most common methods and techniques of prediction, this research employs the following DM techniques:

1. Algorithm for Divisive Clustering
2. Mining Support, Confidence, and Association Rules

3. Results

Production System Behavior Prediction

○ ***Divisive Hierarchical Clustering Algorithm***

Figure 3 shows the model design for data mining. Initially, the entire dataset was assigned to a single cluster. After partitioning the cluster into four similar clusters, the system provided useful insights that were useful for stock control and, as a result, a speedier production plan. With the use of random selection and specifying the predicted 30% cases for testing, the Split input data node divides the initial data folder into data sets for testing and training. A massive data training set was developed as a result of this.

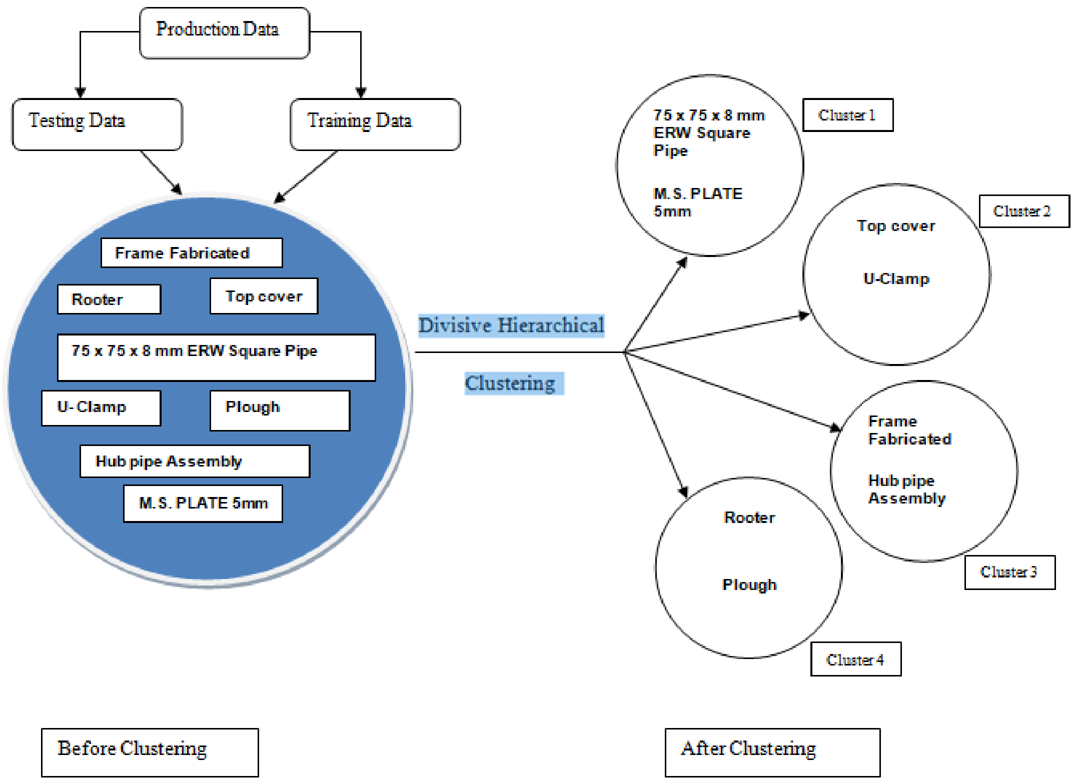


Figure 3: Stock control using Divisive Hierarchical Clustering

```
<script>
$('#submit_btn').click(function(){
    var loc=$('#stock_location').val();
    var puNo=$('#purchase_ref_no').val();
    var ref=$('#ref_no').val();
    var type=$('#stock_type').val();
    var name=$('#item_name').val();
    var qty=$('#stock_qty').val();
    var unit=$('#stock_unit').val();
    var rate=$('#stock_rate').val();
    var cat=$('#stock_mat_cat').val();

    $.ajax({
            url:'saveMaterialStock.php',
            type:'POST',
            data:{loc:loc,puNo:puNo,ref:ref,type:type,name:name,qty:qty,unit:unit,rate:rate,cat:cat},
            success:function(data)
            {
                swal(data);
                window.location.href="RecordStock.php";
            }
    });
});
```

Figure 4: Implementation Summary for stock control using Divisive Hierarchical Clustering

○ ***Support, Confidence and Association Rule Mining***

An association rule has 2 parts: an antecedent (if) and a consequent (then).

"If a customer places an order within the range of the available stock for a day, she's 80% likely of getting the delivery of the requested products. "

Flow of project methodology for Association Rule Mining: As shown in the Figure 5, the system inputs the customer's order. Customer orders should indeed be accepted as internal projects for production planning. The manufacturing team examines the customer's information. Customer requirements are accepted based on priority; however a list of all clients who have placed orders will be available. Customers with the highest priority will be chosen first for Action. Rule of Association Two factors are used in mining: ready for shipment and customer order quantity. Delivery will take place or a strategy should be established for the team to work on based on these two characteristics.

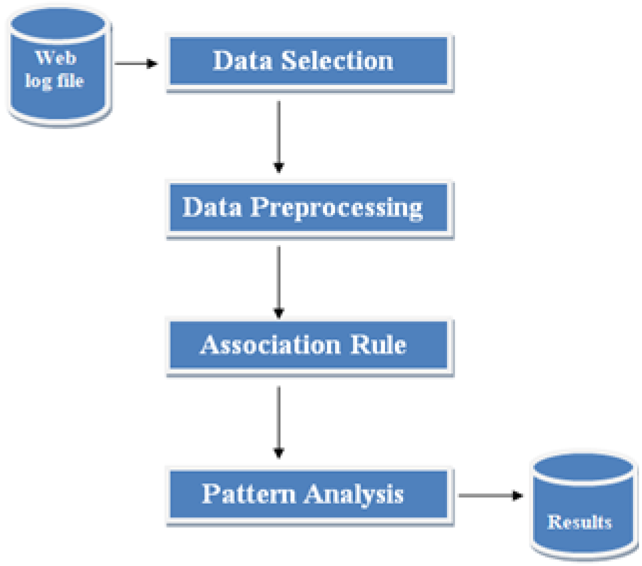


Figure 5: Customer and Ready for dispatch Association Rule Mining

```
var table= $('#example').DataTable({
     orderCellsTop: true,
     fixedHeader: true,
     pageLength : 6,
    'processing': true,
     'serverSide': true,
     'serverMethod': 'post',

    'ajax':{
                'url':'showproductionplan.php'
    },

    'columns':[
                {data:"count"},
                {data:"fname"},
                {data:"cname"},
                {data:"action"},
    ]
});
```

Figure 6: Implementation Summary of Customer and Ready for dispatch Association Rule Mining

Measures of predictive ability of Rule:

X = Customer Requirements count

Y = Ready for Dispatch count (RFD)

$$X \Rightarrow Y$$

$$Support = \frac{frq(X, Y)}{N}$$

$$Confidence = \frac{frq(X, Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

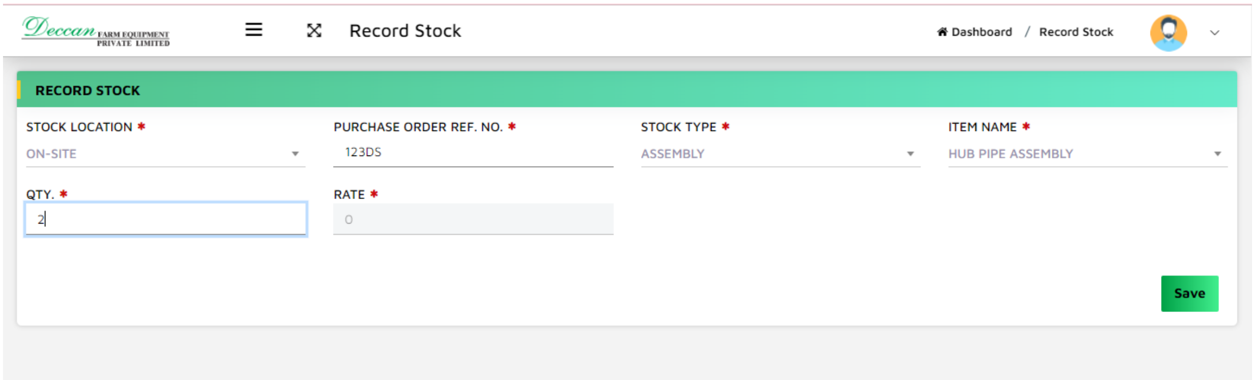
The percentage of Customer requirements vs. stock ready for dispatch is referred to as ***Support***. If they're the same, the factory's production plan is accurate. *Frequency of items bought over all transaction*. The percentage accuracy of a forecast against requirements is measured by ***Confidence***. *How often items X and Y occurred together based on number of X occur. Support (X and Y) / Support (X).* ***Lift***/***Correlation*** is the percentage of times a customer requirement is found with Ready for Dispatch stock versus without it. *Confidence of X and Y over number of Y occur. Confidence (X and Y) / Support (Y).*

4. Evaluation of Result

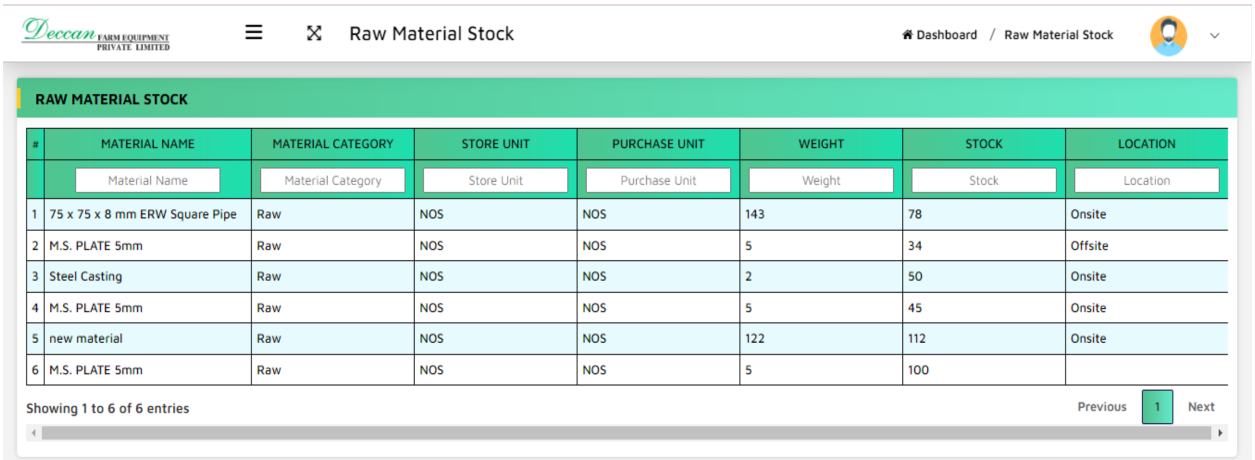
After performing all the individual phases in accordance with the implementation procedure, the final phase uses fresh data to evaluate results. In the deployment first step, segregation was done, followed by the step of Divisive Hierarchical algorithm. The Association method was used to determine the behavior of the system. Screenshots below present the result of Divisive clustering algorithm, considering selected settings. The factory's real - time data was considered, and the results were noticed. The actual test data is shown in Table 1. The data in Table 1 were used to assess the situation. For the association, current real - time data from the manufacturing industry was collected, and the factory's progress was monitored for a month.

Table 1: Expected Test Data

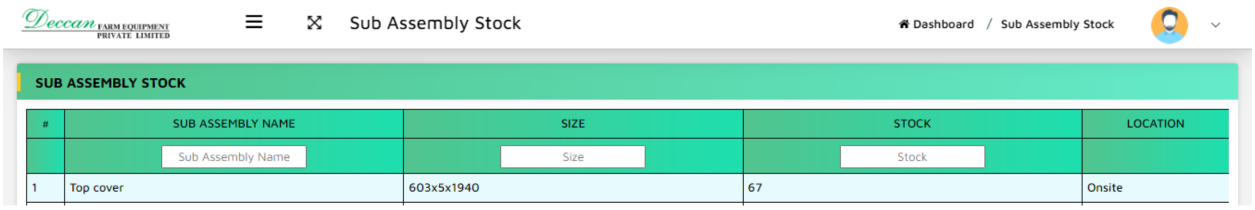
Sr. No.	Part Name	Part Qty.	Material Categoery	RAW SIZE				MTRL.	Material Come from
				OD/L	ID/W	L	Thk./H		
1	**Hub pipe Fabricated**	1	**Fabricated**						
	Hub pipe	1	Round pipe	82.5		568	6	M.S-IS1239	Bandsaw
	Conical hub	1	B/O	As cast				Steel Casting	Vendor
	Plate side hub	1	B/O	As cast				Steel Casting	Vendor
2	**Support Tube Fabricated**	1	**Fabricated**						
	Support tube pipe	1	Round pipe	82.5		725	6	M.S-IS1239	Bandsaw
	Gear box side flange	1	Sheet	205			16	M.S-IS2062	Vendor
	Plate side flange	1	Sheet	175			20	M.S-IS2062	Vendor
3	**Frame Fabricated**	1	**Fabricated**						
	Top cover	1	Sheet	1580	520		5	M.S.-IS2062	CNC Bending
	Top cover Square pipe	1	Sq. pipe	63	63	1581	5	M.S. E.R.W.	Bandsaw
	L.H. Side plate	1	Sheet	545	125		8	M.S.-IS2062	Laser
	R.H. Side plate	1	Sheet	545	125		8	M.S.-IS2062	Laser
	Mounting plate Big	2	Sheet	522	80		10	M.S.-IS2062	Laser
	Mounting plate Small	2	Sheet	522	50		10	M.S.-IS2062	Laser
	Plate for Mudguard	2	Sheet					M.S.-IS2062	Laser
4	**Mudguard Fabricated**	1	**Fabricated**						
	Mudguard	1	Sheet		625	1570	3.15	M.S-IS2062	CNC Bending
	Mudguard Bush	2	Round pipe	28	21	45		M.S-IS1239	Store
	Mudguard Bracket	2	Sheet	195	150		3.15	M.S-IS2062	Iron working
	Mudguard Side Support	2	Sheet	315	70		3.15	M.S-IS2062	Laser



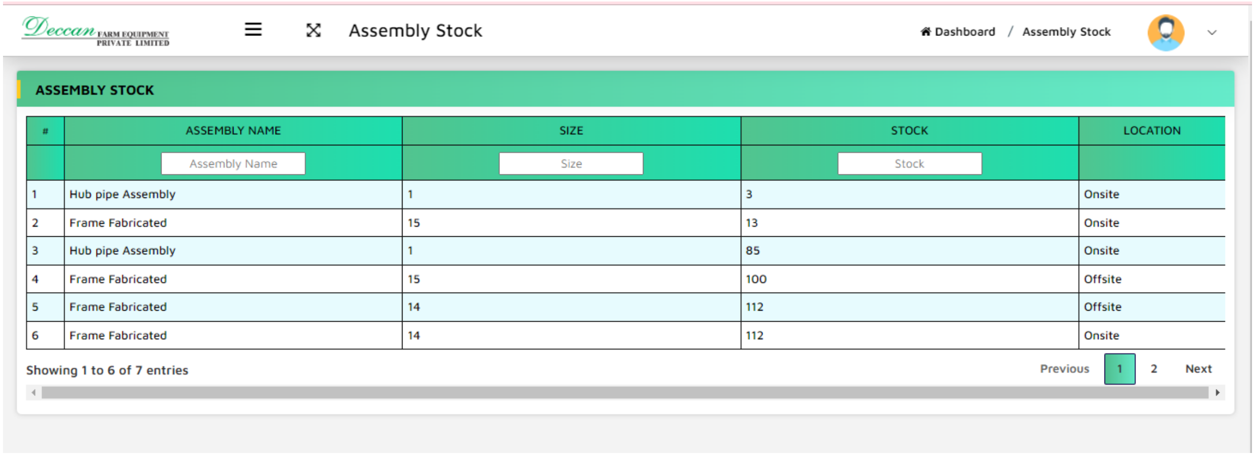
Screenshot 1: Main Cluster



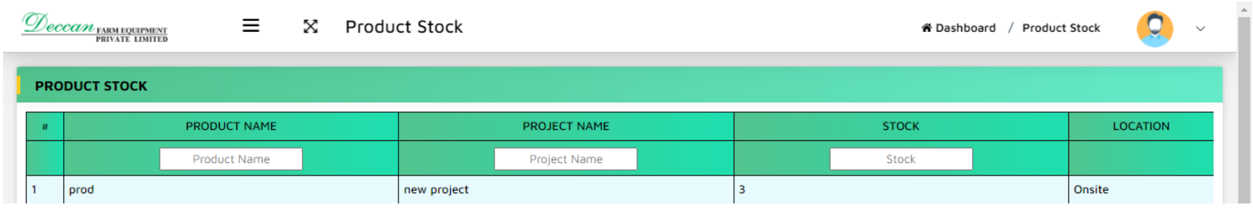
Screenshot 1: Formation of Cluster 1



Screenshot 2: Formation of Cluster 2



Screenshot 3: Formation of Cluster 3



Screenshot 4: Formation of Cluster 4

5. Conclusion

The findings demonstrate the effectiveness of data mining approaches as powerful tools to assist management in making decisions. Using particular determined input parameters, one may clearly predict the future goals and states of the industrial control system based on data from previous managed operations. Managers must have a thorough understanding of the system's behavior in order to exert complete control over it. Managers must understand the interoperability of the parameters used to make system decisions, as well as the influence they have on system performance.

Based on the findings, we conclude that the algorithms chosen are suitable for use in intelligent business solutions. We can confirm the premise that the chosen input parameters may lead to either failing or attaining the desired process objectives when we anticipate the production process and system behavior in accordance with the appropriate KPIs. We can thus forecast the accurate goal values and required outputs for each input with a reasonable level of precision. The prototype model of the actual production unit was used to determine these projected values.

6. Future Research

All future research should focus on looking beyond the point boundary and applying the findings to real - world systems. It could focus on recommending data mining methodology to detect production system issues and attempting to determine the adequacy of the methods examined for specific problem sets. Theoretical approach for discovering knowledge in a hierarchical system utilized for control might be created as a holistic way to address challenges with processing large databases in order to achieve complicated system control.

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Author Profile

Mamata S. Kalas, have been graduate from University Of Mysore, in 1993, From B. I. E. T, Davangere, started her professional career there itself. In 1995, came to kolhapur, after her marriage and since then she has worked as lecturer at D. Y. Patil’s college of Engg., Bharati Vidyapeeth’s College Of Engg., Kolhapur. She did M. Tech (CST) Graduate and her dissertation work is based on image segmentation using parametric distributional clustering. She has been awarded with M. TECH (CST) from Shivaji University, Kolhapur of Maharashtra in June 2009. In November 2019, she received a Ph. D. in computer science and engineering from Walchand College of Engineering, Shivaji University's Research Center, under the supervision of Dr. B. F. Momin. She is currently working as Professor and Head, Dept of CSE at KIT’S College of Engg, Kolhapur. She is in her credit, 27 years of teaching experience. Ten Papers presented for international conferences, three papers presented for national conferences, seven papers published in international journals. Her areas of interest are pattern recognition and artificial intelligence, computer architecture, system programming.

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