Implementation of Decision Tree Learning Method (ID3) Web-Based For Production Optimization (Case Study of Towels Apparel Company)

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Abstract

A lot consideration has take into account to get an effective production activity in a manufacture such as the knowledge and skill of the operator of machine, the quality of machine, time schedulling of production process, quantity of product that has to be finished on schedule, the condition of room and other facilities, and so on. If we fail to manage those condition , it may cause the unstable and ineffective production and this will end up with customer's dissatisfaction. In this research,we were focusing on how to optimize the production process by determining total amount of products , total machine that can be used in one production, time of production and setting the priorities based on those conditions. This optimization will be automatically executed by the web based dessicion support system and this desicion support system adopted the ID3 method.

The ID3 method ,a learning method by building a desicion tree, is used to gain the optimization ,in our case, to optimize the quantity of product , duration of production, number of machine that will be used for each customer's order . Decision Tree Learning methods (ID3) is a method of learning that is very popular and widely used in artifical Intelligents fields.

By building IF THEN statement, calculating entropy and information gain, we can build decision tree. This decision tree is used to get the optimization number of machine that will process the production, quantity of order that will be produced on certain duration of time.

Keywords: Decision Tree Learning (ID3), scheduling the production process, information gain, priorities, entropy.

1.Background

Nowadays, it is impossible to separate the technology from business. The technology especially Information Technology becomes backbones of businesses. By using the IT technology we can easily and effectively manage the existing human and natural resources in production. So the company may improve its revenue and services level to customers and, in the end, it will improve the customer satisfaction.

In our case, we were observing a towel garment called ASRAT company. It is a towel factory that located in Bandung , island of Java in Indonesia that daily produce many kind of towels. This garment had difficulties in determining the number of machine against , quantity order that will be processed and duration of production, further more the company has no idea at all how to determine the schedule of this production process. The lack of management of total demand of products, allocation of resources such as number of machine and duration of production may lead to inefficient and ineffective production process.

We were using optimization method such as ID3 method in our decision support system, hopefully it can resolve those problems. There are many optimization method that have been used widely in trade, industry and so on. We choose the ID3 Method in our research because it is suitable with the codition in our case.

The purpose of this research is to develop a decision support system that can produce optimization among quantity order that will be produced on certain duration and allocation of machine capacity per production. The other result of the system is the list of priority of customer's order that will be process in the garment.

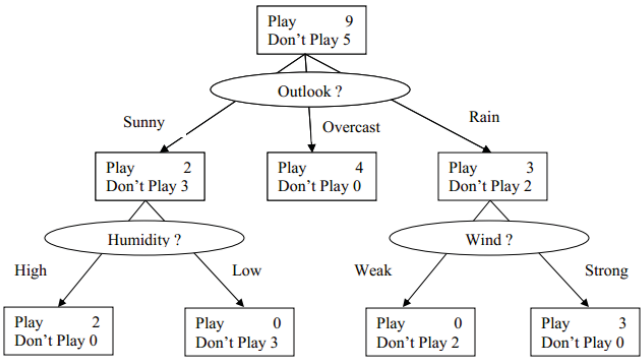
We were focusing our research on :

- How to optimize every production which include the quota numbers of towels , allocation of machine capacity (how many machine that needed for one customer's order) , speed of production (slow until extra fast)
- How to built the decision support system to optimize the production using ID3 method .
- How to develop web based decision support system.

2. Basis Theory

2.1 Decision Tree

A decision tree is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a decision.
The figure below shows an example of a decision tree :



2.2 ID3 Algorithm

ID3 is a simple decision learning algorithm develope d by J. Ross Quinlan (1986). ID3 constructs decision tree by employing a top-down, greedy search through the given sets of training data to test each attribute at every node. It uses statistical property call information gain to select which attribute to test at each node in the tree. Information gain measures how well a given attribute separates the training examples according to their target classification. [3)]

2.3 Entropy

In order to define information gain precisely, we need to discuss entropy first.Let's assume that the resulting decision tree classifies decision into two categories . Those are P(positive) and N(Negative). Given a set, containing these positive and negatives targets. The Entropy is

Entropy (S) = -P(Positive) 2logP(Positive)- -N(Negative) 2logN(Negative) …….(1)
Where :
P(Positive) ; portion of positives examples in S.
N(Negative) ; portion of negatives examples in S

Thus, Entropy is a measure of the impurity in a collection of training sets.

2.4 Information Gain

The information gain, Gain(S, A) of an attribute A, relative to the collection of examples S, is defined as :
.

$$\boxed{Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)} \quad \text{……..(2)}$$

Where :
Values(A) is the set of all possible values for attribute A, and S_v is the subset of S for which the attribute A has value v .

2.5 Building decision tree by ID3 Algorithm

Create a root node for the tree
- IF all examples are positive, Return the single-node tree Root, with label = +
- If all examples are negative, Return the single-node tree Root, with label = -
- If number of predicting attributes is em pty, then Return the single node tree Root, with label = most common value of the target attribute in the examples
- Otherwise Begin
  - The Attribute that best classifies examples
  - Decision Tree attribute for Root A.
  - For each positive value, vi, of A,
    - Add a new tree branch below Root , corresponding to the test A = vi
    - Let Examples(vi), be the subset of examples that have the value vi for A
    - If Examples(vi) is empty
  - Then below this new branch add a leaf node with label = most common target value in the examples
  - Else below this new branch add the subtree ID3 (Examples(vi), Target_Attribute, Attributes – {A})
- End

- Return Root 3)

2.6 An example

:Given an example of ‘PLAY OUT DOOR’ decision. That is a decision of playing outdoor that depend on the Outlook, temperature, humidity and windy attribute.

The symbolic attribute description :

Attribute	Possible Value
Outlook	Sunny, overcast , rain
Temperature	Hot, mild, cool
humidity	High, normal
Windy	True, false
Decision of play out door	n(negative),p(positive)

Table 1: attribute possible values

The learning set of play out door example:

Outlook	Temperature	Humidity	Windy	Decision
Sunny	hot	high	false	N
Sunny	hot	high	true	N
overcast	hot	high	false	P
rain	mild	high	false	P
rain	cool	normal	false	P
rain	cool	normal	true	N
overcast	cool	normal	true	P
Sunny	mild	high	false	N
sunny	cool	normal	false	P
rain	mild	normal	false	P
sunny	mild	normal	true	P
overcast	mild	high	true	P
overcast	hot	normal	false	P
rain	mild	high	true	N

Table 2: learning set

Based on the table 2:
From the whole dataset: there are 5 n(negative) decision and 9 p(positive) decision from total 14 decision.

$$Entropy(S) = -9/14\ {}^{2}\log\left(\frac{9}{14}\right) - 5/14\ {}^{2}\log\left(\frac{5}{14}\right) \ldots\ldots\ldots$$

$$= 0.940 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

From Humidity dataset :

High values

High = 7 , high with p(positive) = 3 , high with n(negative)= 4

Normal values

Normal = 7 , normal with p(positive) =6 , normal with n(negative)=1

$$Entropy(S_{humidity_{high}}) = -3/7\ {}^{2}\log\left(\frac{3}{7}\right) - 4/7\ {}^{2}\log\left(\frac{4}{7}\right)$$

$$=.0.98522 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$Entropy(S_{humidity\_normal}) = -6/7\ ^2\log\left(\frac{6}{7}\right) - 1/7\ ^2\log\left(\frac{1}{7}\right)\ldots\ldots$$

=0.591673……..……(5)

Gain(S,Humidity) $= entropy(S) - \left(\frac{7}{14}\right) Entropy\left(S_{humidity_{high}}\right) - \left(\frac{7}{14}\right) Entropy(S_{humidity_{low}})$

=0.15155……..(6)

2.2 Optimization the production process.

In production activity, we have to consider a lot of circumstances such as maximum capacity of production per machine per working day, number of functional machine, quantity order, periode of time for order fulfillment. Oftenly, The manager has diffulties to determine which of customers order should come first or come last, how many days of production that needed per customers order and so on.

By optimize the production process, hopefully those difficulties can be overcome and it may lead to efficient and effective production activity.

3. Application of ID3 algorithm in the study case

The attributes that involves in our case study are : Quantity order and speed of production

The possible values of quantity order :

Attribute	Possible values in discrete form	Possible values in continues form
Quantity order	Small	100 -5600 towels
Quantity order	Medium	5601-11200 towels
Quantity order	Large	11201-16800 towels

Table 3: possible values of quantity order

The possible values of speed of production

Attribute	Possible values in discrete form	Possible values in real value
Speed of production	Very slow	7 days
Speed of production	Slow	6 days
Speed of production	Quite slow	5 days
Speed of production	Medium	4 days
Speed of production	Fast	3 days
Speed of production	Very fast	2 days
Speed of production	Extra fast	1 days

Table 4: possible values of speed of production

Total number of data is 3 x 7 = 21. We decide to take 15 of the total of 21 data as our learning set to create decision tree.

Order no	Quantity of order	Speed of production	Decision
1	Small	Very fast	YES
2	Small	fast	YES
3	Medium	Extra fast	NO
4	Medium	fast	YES
5	Large	Extra fast	NO
6	Large	Very fast	NO
7	Small	Medium	YES

8	Small	Slow	YES
9	Medium	Medium	YES
10	Medium	slow enough	YES
11	Large	Medium	NO
12	Large	Quite slow	YES
13	Large	Slow	YES
14	Small	Very Slow	YES
15	Medium	Very Slow	YES

Table 3. learning set of customer's order

3.1 Entropy and Information Gain

The symbol of 'YES' decision is '+', and the The symbol of 'NO' decision is '-'.
From the whole dataset: there are 4 N(No) decision and 11 Y(Yes) decision from total 15 decision.
Thus,

$S = [\ 11+, 4-\ ],\ |S| = 15$ ……(7)

From the sub dataset of quantity order with small values
small = 5 , small with Y(yes) = 5 , small with N(no)= 0
From the sub dataset of quantity order with medium values
medium = 5 , medium with Y(yes) = 4 , medium with N(no)= 1
From the sub dataset of quantity order with large values
large = 5 , large with Y(yes) = 2 , large with N(no)= 3
So, we have:

$S_{small} = [\ 5+, 0-\ ],\ |S_{small}| = 5$
$S_{medium} = [\ 4+, 1-\ ],\ |S_{medium}| = 5$
$S_{height} = [\ 2+, 3-\ ],\ |S_{Height}| = 5$……(8)

From the sub dataset of speed with extra fast values
extra fast = 2 , extra fast with Y(yes) = 0 , extra fast with N(no)= 2
From the sub dataset of speed with extra fast values
very fast = 2 , very fast with Y(yes) = 1 , very fast with N(no)= 1
From the sub dataset of speed with fast values
fast = 2 , fast with Y(yes) = 2 , fast with N(no)= 0
From the sub dataset of speed with medium values
medium = 3, medium with Y(yes) = 2 , medium with N(no)= 1
From the sub dataset of speed with quite slow values
quite slow = 2 , quite slow with Y(yes) = 2 , quite slow with N(no)= 0
From the sub dataset of speed with slow values
slow = 2 , slow with Y(yes) = 2 , slow with N(no)=0
From the sub dataset of speed with very slow values
very slow = 2 , very slow with Y(yes) = 2 , very slow with N(no)=0
so, we have:

$S = [\ 11+, 4-\ ],\ |S| = 15$
$S_{Extra\ Fast} = [\ 0+, 2-\ ],\ |S_{Extra\ Fast}| = 2$
$S_{very\ fast} = [\ 1+, 1-\ ],\ |S_{very\ fast}| = 2$
$S_{fast} = [\ 2+, 0-\ ],\ |S_{fast}| = 2$
$S_{Medium} = [\ 2+, 1-\ ],\ |S_{Medium}| = 3$
$S_{quite\ slow} = [\ 2+, 0-],\ |S_{quite\ slow}| = 2$

S_{slow} = [2+, 0-], | S_{slow} | = 2
$S_{very\ slow}$ = [2+, 0-], | $S_{very\ slow}$ | = 2……..(9)

Based on equation no 7 and no 8 we have:

Entropy (S) = - (11/15) $\log_2$ (11/15) – (4/15) $\log_2$ (4/15)
= 0.32814 + 0.5085 = 0.83664

Entropy (S_{small}) = - (5/5) $\log_2$ (5/5) – (0/5) $\log_2$ (0/5) = 0
Entropy (S_{Medium}) = - (4/5) $\log_2$ (4/5) – (1/5) $\log_2$ (1/5) = 0.72193
Entropy (S_{Height}) = - (2/5) $\log_2$ (2/5) – (3/5) $\log_2$ (3/5) = 0.97095 ……..(10)

By using equation no 10, we can calculate Information Gain of quantity attribute as follows:
Gain (S, Quantity) = Entropy (S) – (5/15) Entropy (S_{small}) – (5/15) Entropy (S_{Medium}) – (5/15) Entropy (S_{Height})
Gain (S, Quantity) = 0.83664 – 0 – 0.72193 – 0.97095 = 0.27235 ……..(11)
Based on equation no 7 and no 9 , we have:

Entropy (S) = - (11/15) $\log_2$ (11/15) – (4/15) $\log_2$ (4/15)
= 0.32814 + 0.5085 = 0.83664

Entropy ($S_{Extra\ Fast}$) = - (0/2) $\log_2$ (0/2) – (2/2) $\log_2$ (2/2) = 0
Entropy ($S_{very\ fast}$) = - (1/2) $\log_2$ (1/2) – (1/2) $\log_2$ (1/2) = 1
Entropy (S_{fast}) = - (2/2) $\log_2$ (2/2) – (0/2) $\log_2$ (0/2) = 0
Entropy (S_{Medium}) = - (2/3) $\log_2$ (2/3) – (1/3) $\log_2$ (1/3)= 0.91829
Entropy ($S_{slow\ enough}$) = - (2/2) $\log_2$ (2/2) – (0/2) $\log_2$ (0/2) = 0
Entropy (S_{slow}) = - (2/2) $\log_2$ (2/2) – (0/2) $\log_2$ (0/2) = 0
Entropy ($S_{very\ slow}$) = - (2/2) $\log_2$ (2/2) – (0/2) $\log_2$ (0/2) = 0……(12)

By using equation no 12, we can calculate Information Gain of speed of production attribute as follows:

Gain (S, Speed) = Entropy (S) – (2/15) Entropy ($S_{Extra\ Fast}$) – (2/15) Entropy ($S_{very\ fast}$) – (2/15) Entropy (S_{fast}) - (3/15) Entropy (S_{Medium}) - (2/15) Entropy ($S_{slow\ enough}$) - (2/15) Entropy (S_{slow}) - (2/15) Entropy ($S_{very\ slow}$)

Gain (S, Speed) = 0.83664 – 0 – 0.13333 – 0 – 0.18366 – 0 – 0 – 0 = 0.51965

Since the information gain of speed is greater than information gain of quantity then the attribute speed will be placed on the root of the tree.

3.2. Result and discussion

ID3 algorithm can be used to build a decision tree, in which, the algorithm implements recursive function. In the algorithm we add branch of the tree recursively until the tree is completed and it can classify all data in lerning set accurately.

We can trace the other sample data through the tree, to test wether the sample data has valid result (the sample data has the same value as leaf node value). But sometime, we didn't get the valid result from one sample data, in other word our tree have an error. In that case, we have to improve the tree, by adding some subtree to overcome this error. This improvement is called the overfit tree. Since the information gain of speed is greater than information gain of quantity then the attribute speed will be placed on the root of the tree. The root is the level 0 of tree. Furthermore, we have to check every value of speed , wether the tree need sub tree in level 1 or just add a leaf node.

At recursion of level 0 and iteration 1, we place the very slow branch of speed, and examine the value of verys slow speed dataset.

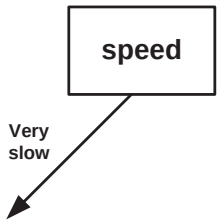


Figure 1.The decision tree at level 0 iteration 1 recursion

At recursion of level 1 and iteration 1, we have the value of very slow speed dataset as : $S_{very\ slow}$ = [2+, 0-], this means the attribute target ='yes' for all sample data of very slow dataset. In other word, for the very slow branch , the tree doesn't need any subtree but the leaf node with 'yes' value.

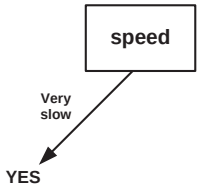


Figure 2.The decision tree at level 1 iteration 1 recursion

At recursion of Level 0 and iteration 2, we place the slow branch of speed, and examine the value of every slow speed dataset.

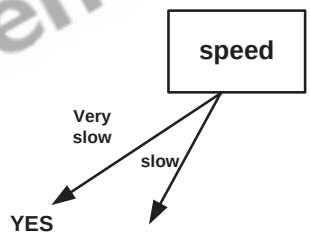


Figure 3. The decision tree at level 0 iteration 2 recursion

Recursion of level 1 and iteration 2, we have slow speed dataset as : S_{slow} = [2+, 0-]. This means atribut target is Yes for every data sample, and there is no subtree for the branch of slow speed .

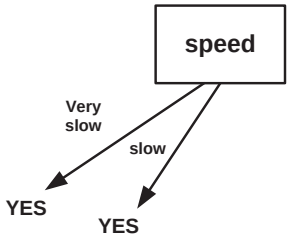


Figure 4. The decision tree at level 1 iteration 2 recursion

At recursion of level 0 and iteration 3, we place the quite slow branch of speed, and examine the value of every "quite slow speed" dataset.

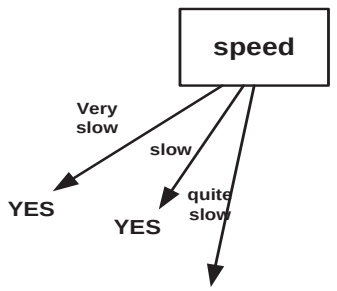


Figure 5.The decision tree at level 0 iteration 3 recursion

At recursion of level 1 iteration 3, , we have quite slow speed dataset as : $S_{quite\ slow}$ = [2+, 0-]. This means atribut target is Yes for every data sample, and there is no subtree for the branch of quite slow speed.

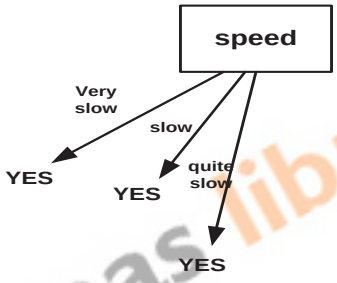


Figure 6. The decision tree at level 1 iteration 3 recursion

The recursion is continue by adding more branch of speed and quantity order, until the decision tree is completed. By using the 15 sample data in the learning set, ID3 algorithm produces a decision tree as shown in Figure7.

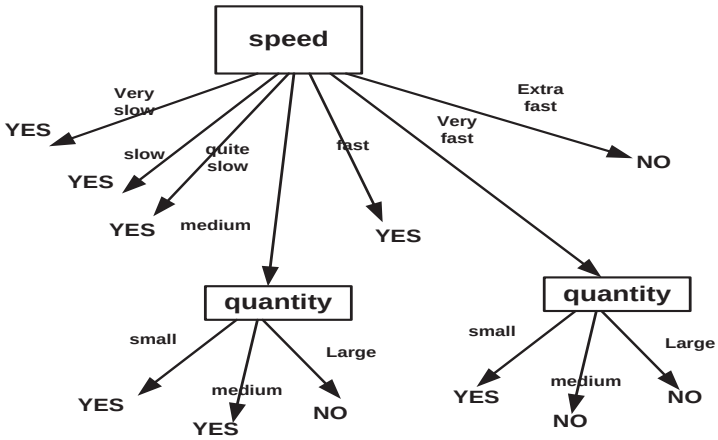


Figure 7. the completed decision tree based on learning set of table 3

Table 4. Six samples of the data that will be tested on the decision tree

Order number	Quantity	Speed	Decision
16	Small	Extra fast	YES
17	Medium	Very fast	NO
18	Height	fast	NO
19	Small	Quite slow	YES
20	Medium	Slow	YES
21	Height	Very Slow	YES

The decision tree can successfully classify the 15 data in the learning set. There are still 6 other data samples that have not been studied in Table 4. The question is : "wether the six datas above can be classified accurately by the tree?" When we tested the order's number of 17, 19, 20 and 21 on the tree, the decision value in the table is the same as the value of leaf node in the tree. But when we tested the order's number of 16 and 18, the value of leaf node is not the same as decision value in the table 4. So we had to fix the leaf node of the fast and extra fast branch . We replace the leaf node of those branch by adding subtree of Quantity. The over fit tree was obtained by adding 2 subtree of quantity and the final tree can be seen in the figure 8.

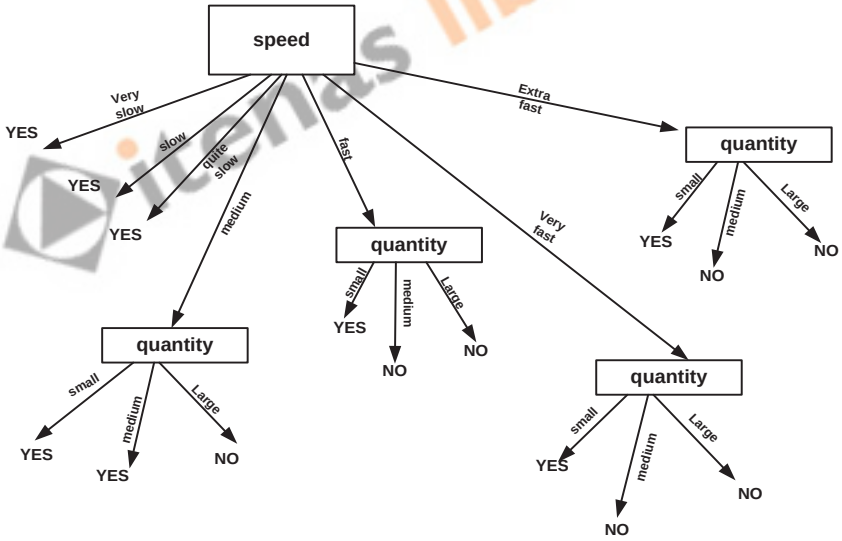


Figure 8.the Decision tree overfit

3.3 Flowchart Application

The flowchart of the overall system is shown in the figure below:

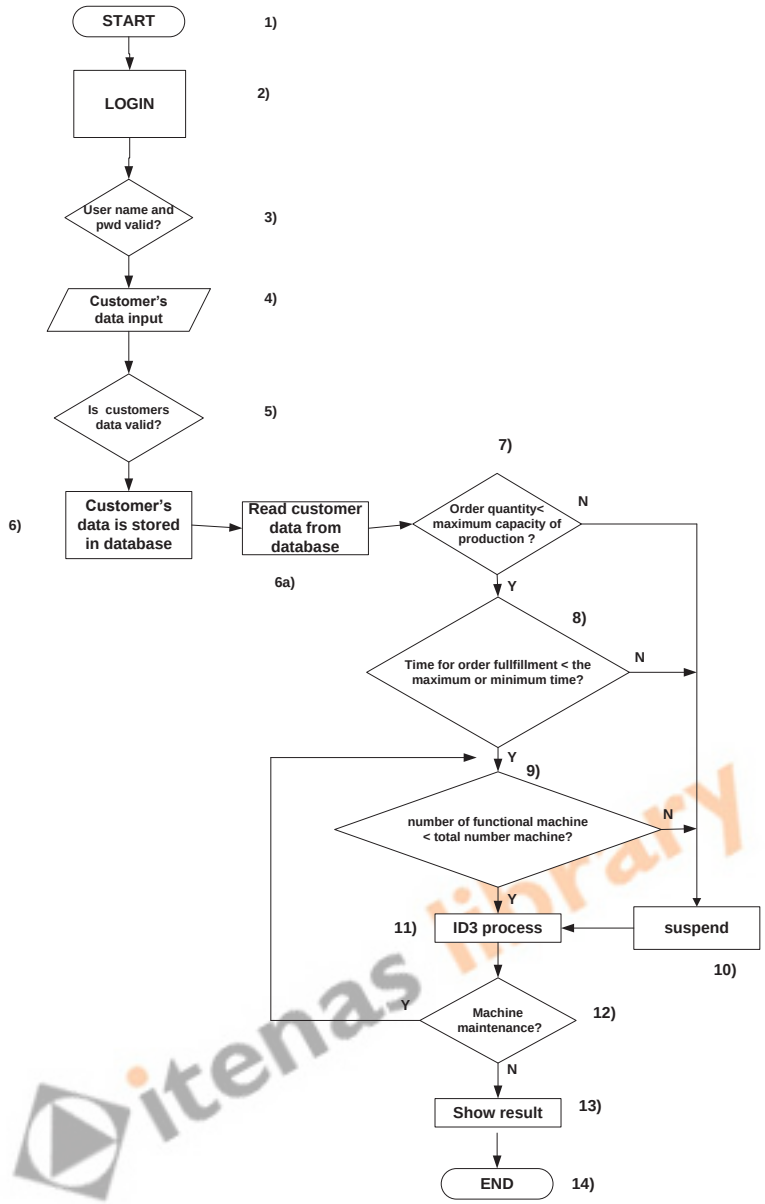


Figure 9. Flowchart of production optimization applications

The explanation of figure 9 is as follows:

1. Start System.
2. Login to the system by entering username and password.
3. If username and password are not valid, then users must enter again until he or she get a successful login.
4. At the system , the users input customer's name, customer's address, order quantity, period of time that the order should be fulfilled, and quantity of functional machine.
5. At this stage, if the user input data is not valid, then the system will asked her or him to input again, until the data is accepted by the system.
6. All of the customer data, that is mentioned in no 4 is stored in the database.
   (6a) The system will read the data or quantity order record that belongs to certain customer from database .
7. This requested quantity order will be checked wether it exceed the maximum capacity of production. If it is still below the maximum capacity then the system will continue to next process (no 8) . If it is greater than maximum capacity of production the system will go to the "suspend" stage , and it will continue to the ID3 process (no 11).

8. At this stage system will examine wether the period of time for order fullfillement is exceed the permitted maximum or minimum production time. If it is still between the minimum and maximum period, then the system will continue to number 9. If it is greater than the maximum or less than the minimum permitted period of time , the system will go to the "suspend" stage (no 10) , and then it will continue to the ID3 process (no 11).
9. The system will examine wether the data input of quantity of machine is equal to the quantity of actively machine. If the data input is equal to the quantity of actively machine the system will go to ID3 Process (no 11).
   If the data input is not equal to the quantity of functional machine the system will go to "suspend" stage (no 10), and then it will continue to the ID3 process (no 11).
10. The execution of ID3 algorithm.
11. The system execute the "suspend" process.
12. At this stage the system examine the numbers of machine that had to be maintained during the production. If the number is greater than 0, the system will go the number 9 again. If the number is less than 0 , the system will continue to number 13.
13. The system show the result of optimization of production scheduling.
14. The flowchart is finished.

3.4. ID3 Process Flowchart

ID3 process is the process of calculating the value of the overall entropy and information gain attributes of each attribute and then formulate a decision tree using ID3.

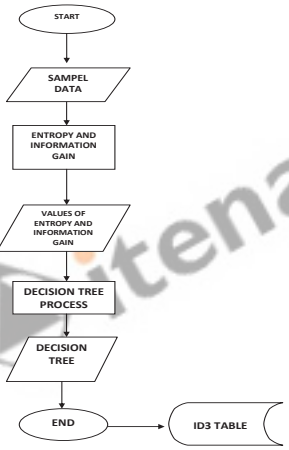


Figure 10. ID3 Process Flowchart

Below is is the explanation of ID3 Process Flowchart in Figure 10. :

1. Start System.
2. Preparation of Data Sample (Learning set).
3. Calculation of the value of Entropy and Information Gain
4. Building the decision tree by using the entropy and information gain value.
5. The results of the decision tree will be stored in ID3 table.
6. Completed.

4. Implementation

We used a test case of a list customer's order of ASRAT towel garment company, which from it we can get the schedule of towel production for three days in a row Since the number of functional machines were limited, without the system support, the manager would have many difficulties to determine which customer's order come first or come last in the production scheduling.

Table 3. Customer's order as an example input

No	Customer's name	date of entry(order date and time)	Duration (days) for order fulfillment	Quantity order
1	Indomaret	5 Pebruary 2011 05:10:11	1	300
2	Alfamart	5 Pebruary 2011 05:10:29	2	200
3	Giant	5 Pebruary 2011 21:39:18	2	500
4	Yogya Market	5 Pebruary 2011 21:40:12	2	600
5	Carefour	5 Pebruary 2011 21:40:52	2	1.500
6	Alfamidi	5 Pebruary 2011 21:41:26	2	500
7	Ramayana	5 Pebruary 2011 21:42:29	3	2000

Note:

- ✓ The maximum production per working day is 2240 towels .
- ✓ The number of active production machine for 56 machines from a total of 60 machines.
- ✓ Each machine can produce 40 towels a day.
- ✓ The machines that going through a maintenance were:
  - machine no 1 maintained for 3 days.
  - machine no 2 maintained for 3 days.
  - machine no 3 maintained for 2 days.
  - machine no 4 maintained for 1 day.

The result of the system is shown in figure 11.

The schedule of towels production with 2240 towels maximum of production per day is:

1. 7 February 2011
   Indomaret's order : 300 towels as total of order quantity will be completed.
   Afamart's order: 200 towels as total of order quantity will be completed.
   Giant's order: 500 towels as total of order quantity will be completed.
   Yogya's order: 600 towels as total of order quantity will be completed.
   Carefour's order: 640 towels as part of order quantity will be completed the rest 860 will be completed in the next day.

2. 8 February 2011
   Carefour's order: 860 towels as part of order quantity will be completed. Alfamidi's order: 500 towels as total of order quantity will be completed.
   Ramayana's order: 920 towels as part of order quantity will be completed
   the rest 1080 will be completed in the next day.

3. 9 February 2011
   Ramayana's order: 1080 towels as part of order quantity will be completed

Figure 11. Status of the Optimization Process

description and date of production.Users can determine the order of which must be done in advance of production and its quantity in Figure 11, and can be seen also consumer data,

5. CONCLUSION

Based on the result of the implementation that is shown in figure 11, we can conclude that towels production scheduling on towel ASRAT garment companies can be optimized by using ID 3 Decision Tree Learning. The optimization of the towels production scheduling included the order of production of customer's request, quantity order of a customers that can be produced a day, period of time of order fulfillment. For example, the customers Ramayana need two days of production.

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