Data Mining Application in Process Control of Smart Material Manufacturing

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Abstract: According to Industry 4.0 concept, huge amounts of data is generated in Smart Material Manufacturing and this data needs to be collated, stored, organised and analysed in order to develop a more efficient manufacturing system. This study focuses on the prediction of smart material manufacturing process, based on the current production data. It presents a route of knowledge gain about predicting future manufacturing systems, using data mining. The model proposed for the actual manufacturing process is made to acquire the necessary data for process control. Implementing particular methods of data mining, and by altering the input parameters, we can predict the behaviour of the manufacturing processes. This prediction is then verified by the use of a simulation model. After analysing various methods, the method using neural networks is chosen for deployment of the latest data in the concluding phases. This research aims at designing and verifying the tools for mining data for supporting system control in manufacturing. It aims at improvement of the process of decision making. The practical control strategies can be accurately modified, depending on the predictions made and the targeted results of production. These strategies can then be used in real time manufacturing, without a chance of failure.

Keywords: Smart Material Manufacturing, Simulation, Forecasting, Data Mining, Decision Support, Process Control.

I. INTRODUCTION

Data is the new oil and collection, storage and processing of data has found its way into all walks of life; manufacturing of Smart Materials being one of them. Industries collect their data into Data Warehouses, but extracting usable data from this stored data is of importance. In order to predict trends, data analysts need to acquire viable information from the data. The outcome of this analysis is used by efficient managements for making informed decisions and plans for the future strategies. Repa (2007) calls this process as knowledge management and it is performed by data analysts.

Tsai (2013) describes the correlation between data mining and knowledge management. The techniques of data mining and knowledge management enables the domain experts to make informed decisions, supported by added knowledge, giving them an edge over the competition, as explained by Tsai (2013). The end users of these systems are managers of all levels, and business owners. Data Mining is a domain that covers various disciplines, with the targets of outcome prediction, data relationship revelations, encouraging application of tools and techniques that are automated, making use of refined algorithms, discovering hidden structures, irregularities, and patterns from a huge database stored in a warehouse. In data mining, the two major goals are describing and forecasting. Explanatory data mining discovers useful patterns for description of the data, while as data mining for forecasting aims at prediction of a behavioural model for pre-determination of future key variable values, basing their findings on the currently available information in the databases available. According to Choudhary et al. (2006), there are no sharp margins between the predictive and descriptive forms of data mining.

II. MODERN MANUFACTURING

The conducted surveys in modern manufacturing, by KDnuggets (2014) and by Rexer Analytics (2010) earlier, manufacturing does not utilise data mining very often. The use of data mining in manufacturing of smart materials is lesser than 10 percent. Feng et al. (2006) lays the background theory for using data mining in production planning, logistics and manufacturing processes. In recent time, there has been a fairly extensive review of the use of data mining in manufacturing of smart materials. Bubenik et al. (2014), Trnka (2012) and Choudhary et al. (2009) include various application possibilities of data mining in production processes like planning, scheduling, diagnosing faults, quality control, analysing defects, decision support system and supply chain management. Dengiz et al. (2006) has some precise instances of applications of data mining in manufacturing, like analysing defects in manufactured ceramics. Da Cunha et al. (2006) also suggest a possibility of the use of production data to determine an efficient assembly sequence and reducing the risk of faulty product production. Kusiak (2006) presents a number of other examples of applications of data mining in medical industrial and pharmaceutical manufacturing industries. A new framework for classification of theoretic decisions was developed by Braha et al. (2007), which was then applied to a real time manufacturing line of semiconductor wafers.

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Huyet (2006) used an approach similar to this for suggesting the analysis and optimization of production systems in a simulated manner. This paper focuses on using method of data mining in control of smart material manufacturing processes.

The goal of this research is predicting the systems performance used for producing smart materials, based on input parameter changes. These input parameters are representative of the control variables that define the specified control strategies. These input parameters are their relation with each other, affect the manufacturing systems' performance, according to Li et a. (2009). The production system behaviour evaluation will be done by application of major number of product qualities of the methods used in the manufacturing arrangement. Grabot (1998) defines the indicators of the performance of the production process.

III. METHODOLOGY

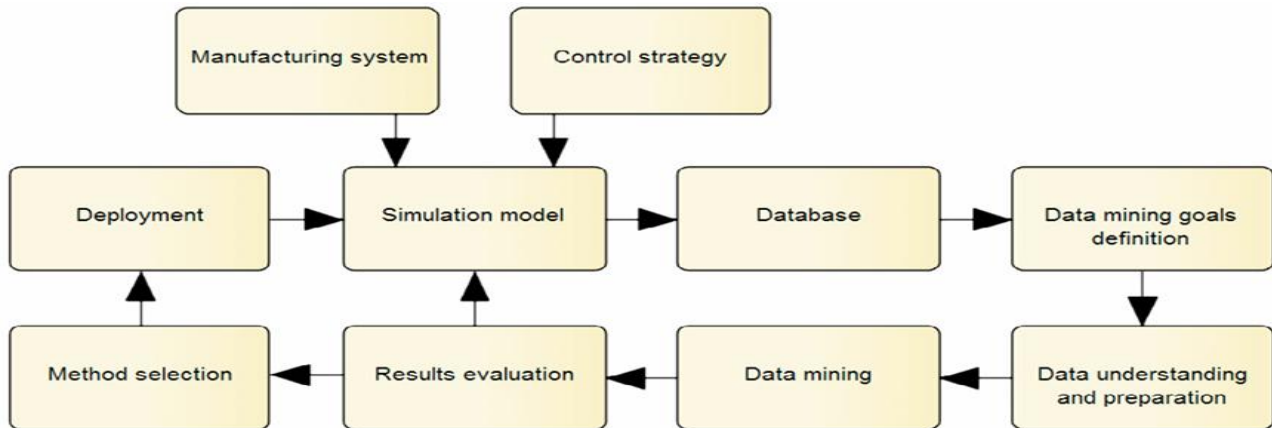Figure 1 presents the process for implementation of the system. Each of these steps is described further

Fig. 1: System Implementation Procedure

- *Manufacturing Process Description*

In this case study, a manufacturing process in an automobile industry part supplier is dealt with. In this organisation, there was a need of proposing a prediction paradigm for certain outputs of the system, as it's important to measure the affect of the fast as well as regular change in the input boundaries in the method of manufacturing. Production unit under analysis manufactures two types of products simultaneously. The inputs to the system are the orders received, which are then manufactured in different sized lots at varying time intervals of the input. Figure 2 shows the two dimensional representation of the model for simulation. In this system, we represent a system for a production unit, using batch manufacturing, which is then executed in the simulation.

This production unit had 5 technical manufacturing workplaces and two quality checks for the output, each for the final two products. 1 to 4 workstations consist of two machines for CNC. For each workplace, both outputs and inputs have buffers, which serve as storages that are interoperable. The production batches are transported on vehicles that have precise and distinct tracks which further join these workplaces. The flow of materials for both the products depicts the technical processes and the predefined schedule for operation. Figure 2 also presents the orientation of the material flow.
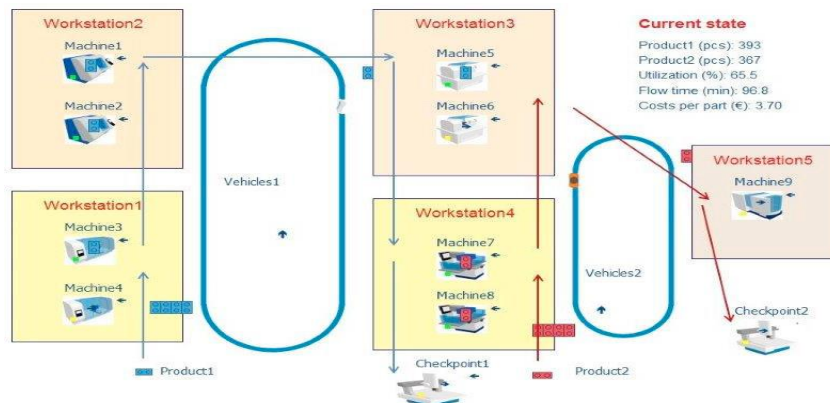

Fig. 2: Smart Manufacturing System Material Flow

• **Prototype Model**

A prototype or simulation was used in this project to generate the data of production as the required data was unavailable. This simulated replica was in addition, used to verify the outputs obtained because of the high threat of practical verifirte in a production unit. For building the simulation model, simulation principles from separate events were used and the production system model was developed in Lanner Group Witness Simulator (2016).

The present condition of the manufacturing process was used as the input information. This included various output variables like machine conditions, number of operations, buffer state, KPIs, KRIs and transport device state. All these separate parameters of the output were determined by entities in the simulation model of discrete events.

This model helps in calculating of the KRIs and KPIs in case the said event occurs and the technical operation is concluded. This leads to an accurate calculation of the KRIs and KPIs, which can be concluded from the validation process. The real system is used as a benchmark to validate the simulation model. The validation process has much iteration to compare the simulation to the real system's behaviour and results. In the end, an exact model of the actual unit is obtained by calibrating the simulation. It is treated as a closed unit, keeping its form unchanged for the sake of the next step of the analysis. Witness Experimental module was used to generate the data.

For the given scenarios, the input parameters had the following possible ranges:
1.   A lot size between 1- 10 pieces
2.   An input interval of 5 – 35 minutes

These scenarios were constituted from multiple instances and the responses thus received were defined as the functions of the simulation model, representing the given KPIs. These simulation runs lasted for one month, without the scenarios being replicated.

• *Strategy for Control*

The control strategy for the simulation is supposed to reach certain goals set for the production. In Parmenter (2009), set of measures that focus on the performance of the organisation is represented by KPIs, which are of prime importance in the present and future excellence of the organisation. In this case study the focussed KPIs are measured in a short period and include total finished products, under production products, time of production, Capacity utilization and Key Result areas, including the cost per unit. Parmenter (2009) suggests that these indicators have a considerable impact on the process being observed and affect the observed process' performance in a positive manner. Simultaneously, all these key indicators are monitored for fulfilment.

The input production parameters need to be adjusted appropriately for reaching the efficiency in production and to achieve the required production objectives. A model is constructed, which describes the intricate associations between various settings of input constraints and constructs the goals of the control plan. Further assessment of the objectives and standards of the production process was made, based on the separate production objectives and their quantitative characteristics. Five indented features with their assessment done quantitatively were chosen. The objectives and features are only suitable for one precise production scheme and for a certain period. As the specified strategy conditions are fulfilled by the process, we can consider that the manufacturing goals are fulfilled too. The total goals includes a per unit cost of 5 units, more than 600 finished products and a flow time of less than 110 minutes. This had to be achieved at a utilization capacity of more than 60 percent and at one time, less than on equal to 4 pieces had to be worked on. This variable maybe right or wrong, as depicted in Table 1.

Table 1: Predicted Data

	1 Costs per part	2 VD1	3 VD2	4 V1_time	5 V2_time	6 Num. of products	7 Flow time	8 Utiliza-tion	9 W.I.P.	10 Total goals
1	4.985	3	3	15	8	760	133.79	68.929	5.319	FALSE
2	4.141	3	3	15	9	760	96.731	65.765	3.149	TRUE
3	3.502	3	3	15	10	759	61.517	62.865	1.511	TRUE
4	3.236	3	3	15	11	738	44.702	60.083	0.801	TRUE
5	4.157	3	3	16	9	740	96.682	64.028	3.130	TRUE
6	3.498	3	3	16	10	739	61.497	61.087	1.493	TRUE
7	4.173	3	3	17	9	722	96.609	62.501	3.110	TRUE
8	4.166	3	3	18	9	709	96.573	61.077	3.092	TRUE
9	4.726	3	4	15	11	761	125.83	68.412	4.759	FALSE
10	4.130	3	4	15	12	759	99.134	65.83	3.253	TRUE

If The Total Goals variable is true, then we can conclude that all the goals are being fulfilled by the process. If otherwise it is False, then all the goals aren't met simultaneously.

• **Database**

The data obtained in the individual runs of the simulation models represent the values achieved by the chosen parameters of the goals and the control parameters' input variables while monitoring the production system. For every model run, the time interlude set was until a month. The RDBMS selected to record the process data generated was Oracle 12c.

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- **Methodology Used**

As shown in figure 1, the methodology used for this analysis was CRISP-DM, whose Fast operation component lets it to be used in models that have been used before on relatively newer dataset.

Due to this module, we can rewrite the variables for predicting the values depicting the dataset for input, in addition to the data warehouse or the external database. The output from these methods is the PMML document, which gives a standard process for representing models for data mining.

According to Statsoft Inc. (2013), these prototypes may be pooled by various modules. For the prototype model suggested in the simulator, 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 in the PMML are usable for making decisions to control the process. This evaluation is described in the results.

- **Methods of Mining Data**

To correctly apply the solved problem of prediction, we need methods and techniques of cognition. Rexer Analytics (2010) and KDnuggets (2014) give survey results in tandem with the data mining processes and the real time data available. This forms the basis of the decision of prediction implementation through the most common methods and techniques of prediction, as follows:

1.	Random Forest (RF)
2.	Boosting Tree (Boost)
3.	Multiple Regression (MR)
4.	Standard Classification and Regression Trees (CART)
5.	Neural Networks (NN)
6.	Support Vector Machines (SVM)
7.	Multivariate Adaptive Regression Splines (MARS)
8.	K Nearest Neighbour (KNN)

- **Metrics used in Data Mining model assessment**

There are many ways, both simple and complicated, for determining the efficiency of the categorical prediction models. Various classification metrics and regression oriented metrics like the ratio of correct classification, general accuracy, lift charts, rate of error and good-fit were used in the analysis. Ratio of the total correct predictions means the general accuracy. Precision or positive predictive value is the ratio of positive cases that are identified correctly. On the other hand, the ratio of correctly identified negative cases is the negative predictive value. A gauge of efficiency for a categorization model, that is obtained when proportion of conclusions reached through the model and by omitting the model is known as the Lift chart. These are graphic aids for performance evaluation in classification models.

When the Statistica programme computes the average residual squared error in the individual prediction models, the error rate for problems related to regression, is the values observed for the existing outcome variable. We calculate overall error rated in case of classification related problems. A Good fit calculation uses Percentage disagreement, G-square statistic and Chi-square statistic for categorization models. In mathematical forecast, the measurements commonly used are correlation coefficient, mean square error, mean absolute error, and relative mean squared error, as suggested in Statsoft Inc. (2013).

## IV.	RESULTS

- *Production System Behaviour Prediction – Classification*

Figure 3 shows the model design for data mining, using the shortlisted classification process. The resultant designed model comprises of Total goals, which is the categorical dependent variable. The predictors in this case are continuous variables that can be controlled, with lot sized VD1 and VD2, with respective time gaps of time V1 and time V2.
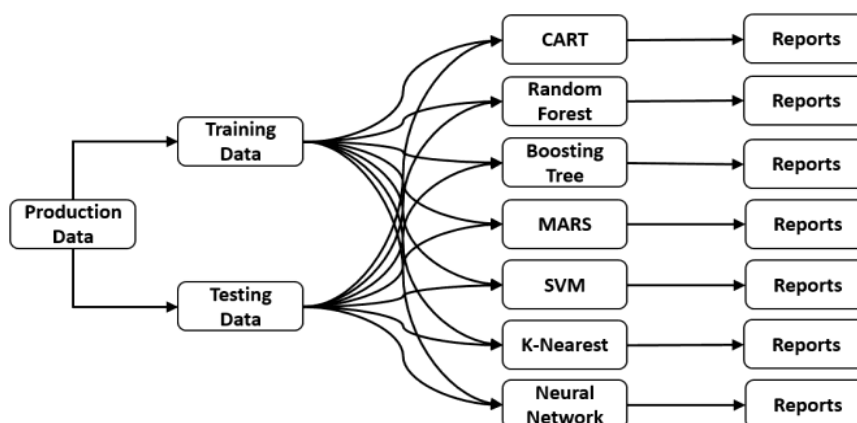
Fig. 3: Classification Model of Data Mining – Design

The initial data folder is segregated by the Split input data node, into data sets for testing and training with the use of sampling at random and setting the estimated 30% cases for testing.

A training set was hereby created, which constituted of 1395 notes, for a test set of 586 notes.

The data mining model hence developed was used on this processed data set and subsequently, the classification accuracy was observed by using the test data to obtain results in every model.

Table 2 was created using these results of all the processes, to depict the order observed in the success model for given metrics.

To evaluate the results obtained, we used the statistical-mathematical method of scoring for multiple objective evaluations. From 1-7, the points and orders were evaluated and assigned starting from least winning process to the most winning process in the metrics.

Table2:Classification Methods Order Summary

	NN	Rand	CART	KNN	SVM	Boost	MARS
Overall accuracy	1	2	3	4	5	6	7
Correctly classified TRUE	1	3	2	4	5	6	7
Correctly classified FALSE	1	3	2	4	5	6	7
Error rate	1	2	3	4	5	6	7
Lift chart	1	3	2	4	5	6	7
Chi-square	1	3	2	4	5	6	7
G-square	1	3	2	4	5	6	7
Percentage disagreem.	1	3	2	4	5	6	7
Summary	8	22	18	32	40	48	56

The worst score was 56 and the best score was 8, which was reached by eight metrics and seven models. The best method was the one that was assigned the lowest number of points and the worst method was the one with the highest points.

After comparing and evaluating all the method, the new data set classification was chosen to be done by the NN method. The output and hidden layers and the number of input neurons in NN was set to the specified task automatically. This task was defined by output values, data set for input and input parameters. The best results for all metrics were obtained by neural network.

- *Regression – Numerical Prediction*
Numerical prediction of the manufacturing goal indicator is used to monitor the system behaviour. The models created can be used for predicting the quantitative values, depending on correlation among various positions of organized parameters that are input individually, and the manufacturing goals. For each production goal, a numerical prediction is made in particular. Every model for data mining has related perpetual variable, which represents the manufacturing goal indicator

and the size of the lot predictor Vd1 and Vd2 and their respective time gaps of input. Individual models for mining data (5) were developed for every manufacturing goal, like finished product count, per part cost, capacity utilization, manufacturing duration and products with under production or semi-ready products. On every transformed set of data, every data mining prototype created was used. Subsequently, the accuracy of prediction was calculated depending on various figures from the outcome of test case data set. For evaluating the models a Module with Rapid Deployment was used. At first, the mean squared error residual or the error rate was evaluated. Table 3 presents the different procedures in an ascending order.

Table 3: Cost per part Error Rate

	Error rate
NN	0.001600
KNN	0.018314
CART	0.021583
RF	0.026241
SVM	0.052129
Boost	0.144016
MARS	0.166651
MR	0.166850

Table 3 has the fault forecast of the models chosen in the set of data used for testing. If the error has a smaller value, it indicates that the model is more powerful and better. The NN model achieved the lowest residual error in this case. In addition to this, in accordance with the metrics of fit in numerical predictions, every model's accuracy may be contrasted. Table 4 lists the procedures in an ascending manner, with respect to obtained standards in separate figures. When NN was used, the error in the prediction was the smallest and hence it is the most appropriate answer.

Table 4: Good-Fit in Varying Cost for Each Part

	Mean square error	Mean absolute error	Mean relative square error	Correlation coefficient
NN	0.0030243	0.0412196	0.0001731	0.9955259
CART	0.0196653	0.0816930	0.0012026	0.9706029
KNN	0.0364194	0.1252114	0.0021226	0.9477075
SVN	0.0506216	0.1813791	0.0032855	0.9253509
RF	0.0685247	0.2017735	0.0042767	0.9231864
Boost	0.1632220	0.3192827	0.0112108	0.7250672
MARS	0.1639706	0.3263381	0.0115438	0.7196053
MR	0.1740447	0.3352871	0.0122151	0.6990720

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V. EVALUATION OF RESULTS

After performing all the individual phases in accordance with the implementation procedure, the final phase uses NN method to deploy fresh data through files of PMML.

In the deployment first step, segregation was done, followed by the step of numerical prediction or regression. The classification method was used to determine the behaviour of the system. In Table 5, we present the result of classification of the input parameters, considering selected settings. By using the NN method, the value True was assigned to the initial three settings. This meant that the succeeding fulfilment of every characteristic was predicted, rendering the process including first 3 settings, successful.

Table5: New Data Predicted Categorically

Set of parameters	VD1	VD2	V1_time	V2_time	Total goals
I	3	7	10	21	TRUE
II	5	4	15	19	TRUE
III	6	3	16	18	TRUE
IV	7	5	20	11	FALSE
V	8	6	18	20	FALSE

When parameter IV and parameter V were set, it was not enough to acquire the required quality for all the goals of manufacturing, simultaneously. Table 7 shows the verification of the classification while using the simulation. Considering the individual features values acquired by the simulation, we can consider that the required goals of the managerial strategy are fulfilled. In table 6, we detect the specific indicator values, rounded to two places of decimal.

Thus the values predicted confirm the preceding classification. In cases V and IV, the parameter setting did not simultaneously fulfil the goal as they did not fulfil the requirement of the products in manufacturing. Mainly, the maximum number of pieces in buffer should be 4 and the manufacturing flow time should not exceed one hour and fifty minutes.

Table 6: Values Predicted after setting new Parameters

Set of parameters	I	II	III	IV	V
VD1 [pcs]	3	5	6	7	9
VD2 [pcs]	7	4	3	5	6
VD1 time [min]	10	15	16	20	18
VD2 time [min]	21	19	18	11	20
Costs per part [€]	3.93	3.27	3.39	5.67	4.30
Num. of products [pcs]	912.54	822.01	844.50	977.08	1048.97
Flow time [min]	107.78	54.24	60.78	212.12	145.24
Utilisation [%]	80.54	72.25	73.17	92.83	93.16
W.I.P. [pcs]	4.00	1.10	1.68	9.52	6.15

In Table 7, the last column shows the total goals, which showed that each setting's classification was confirmed by the simulation. These values of the row are similar to those of the same column of table 5. Thus the NN method gives the most successful classification. Subsequently, we compare the numerical values pertaining to prediction and the simulation, in Table 6 and Table 7.

Table 7: Simulation based Values

Set of parameters	I	II	III	IV	V
Costs per part [€]	1.01	3.27	3.35	5.77	4.19
Num. of products [pcs]	907	841	835	973	1043
Flow time [min]	110.38	55.68	57.07	212.10	134.25
Utilisation [%]	80.05	71.71	72.47	90.96	92.63
W.I.P. [pcs]	3.99	1.40	1.52	11.15	6.03
Total goals [0/1]	TRUE	TRUE	TRUE	FALSE	FALSE

The largest differences were found while predicting the finished products numbers. There was a difference of 4-19 pieces between the predicted and the actual values from the simulation, using the NN method. This gave an average deviation of 0.95 percent. The prototype verified that the procedures selected were elaborately described for every manufacturing result that was desired. There was a high accuracy of the cost per unit prediction, which showed an average divergence of 1.5 percent.

Time of flow prediction was in addition to the point, with a deviation of 11 minutes at the maximum. The capacity utilization values predicted were accurate too, with a maximum deviation of 1.87 percent for IV parameter. The highest deviation of 1.63 percent was found in the work in progress prediction for IV setting, with a difference of 2 units.

For a smart material manufacturing system, the deviations may be acceptable, but require a better precision to acquire near perfection.

VI. CONCLUSION

The results achieved show the efficiency of data mining methodologies as powerful tools in support of the Decision making process by the management. Depending on the data in the past, pertaining to the controlled processes, one can clearly predict the future goals and states of the manufacturing control system, using certain chosen input parameters. It is imperative for managers to completely understand the behaviour of the system, in order to establish complete control on it. Managers need to comprehend the interoperability of the parameters for decisions in the system, in addition to the impact they have on the system performance.

Judging by the results, we draw the conclusion that the PMML files selected by using the NN method for classifying and for numerical predictions are appropriate for their implementation in the intelligent business solutions. When we forecast the production process and system behaviour in tune with the required KRIs and KPIs, we can confirm the hypothesis that the chosen input parameters may lead to either failing or achieving the desired process objectives. With a tolerable accuracy, we can thus predict the accurate goal values and the required outputs for each input. These projected values were established on the prototype model of the actual production unit.

FUTURE RESEARCH

All research in future can focus on studying additional to the point boundary and applying the outcomes obtained into actual systems. It may centre on recommending the data mining methodology to identify the production system problems and attempt to establish the aptness of the methods analysed for specific problem sets. Theoretical proposal for discovering knowledge in a hierarchical system used for control may be developed as a holistic method to solve the issues pertaining to processing huge databases to achieve a system control that is complex.

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