Using Data Mining in MURA Graphic problems

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***Abstract*—The MURA phenomenon will result lots of problems in Photomask and TFT-LCD industries as well. In this paper, we designed and developed a MURA related association rules which suitable for the MURA model requirements, and we named MURA Risk rating system. Our purpose is to figure out the effective application of data mining algorithms in monitoring and control of complex Large Area Photomask systems. By combining the Data Mining into MURA risk management. It could be suitable not only for every Photomask company but also companies facing to the MURA problems. And through our scheme and MURA risk rating system, we can shorten the time and reduce the MURA problems. It could also help them to cut down their manufacturing cost as well as promote the quality of their products.**

***Index Terms*—Large Photomask, MURA, Data Mining, Data Mining application**

I. Introduction

The effective and efficient management and use of increasing amounts of stored data and in particular the transformation of these data into information and knowledge, is considered a key requirement in modern information systems.[1]Data Mining is concerned with the different applications for discovery of a priori unknown relationships such as associations, groupings, and classifiers from data. Data Mining is one component of the broader process known as Knowledge Discovery in Databases (KDD) [2]. Federal agencies use data mining to monitor cell phone communications via satellite. Compaq uses data mining to examine calls made to customer service to find patterns of complaints [3].

The goal of Data Mining is to discover knowledge hidden in data repositories. With this characteristic, finding the association rules or the algorithms for learning classifiers from relational data is the solution of MURA problems in producing to the large Photomask industry.

Photomask is a very important part in the semiconductor industry's production, and the quality of Photomask depends on the precision of laser-generated graphics. The quality problems of Photomask cause the MURA phenomenon in LCD panels [4]. The cost in mask manufacturing is as high as 6 million to 10 million NTD, how to reduce mask defects of their production and shortening the waiting time for machines' adjustment are the key issues for mask production plants to maintain competitiveness with others. Basic in this concept which fallows as: expert-select, database and optimization mining [5]. It could be provide not only for every Photomask company but also companies facing to the MURA problems. This will help them to cut down their manufacturing cost as well as promote the quality of their products.

In this paper, we designed and developed a MURA related association rules which suitable for the MURA model requirements, and we named MURA Risk rating system. Our purpose is to figure out the effective application of data mining algorithms in monitoring and control of complex Large Area Photomask systems. In order to enhance the quality of Large Area Photomask, this paper will concentrate on how to connect the Data Mining Techniques with MURA problems.

II. The MURA Data Warehouse

A. expert-select database

The first process of Photomask manufacturing is transformation, augmentation, and verification. And it follows five steps: receive data, view and edit, conversion, data approval, send to writer. If we hypothesize the MURA problem is caused by graphics array, before the data send to writer, we should make a descriptive data summarization of the graphics input data and hierarchy the generation of the graphics data. As we know, the data format have to change into the conversion center which made the lithography could read. We chose one of them to make it as our input database format to ensure our measurement is the same. In this case, we take the GDSII

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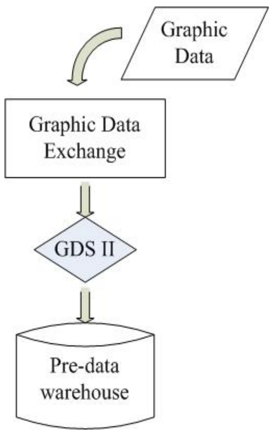

Figure1. Data process model

as our input indicator which can be easily giving it computable coordinates. And this will become our pre-data information (see Figure1).

The laser writer has lapped over each array graphics to build a larger area Photomask. We know the lithography lap in two directions which is x-axis and x-coordinate. It could composite the vector graphics. And it defines a three-dimensional mining which may include the time-series data.

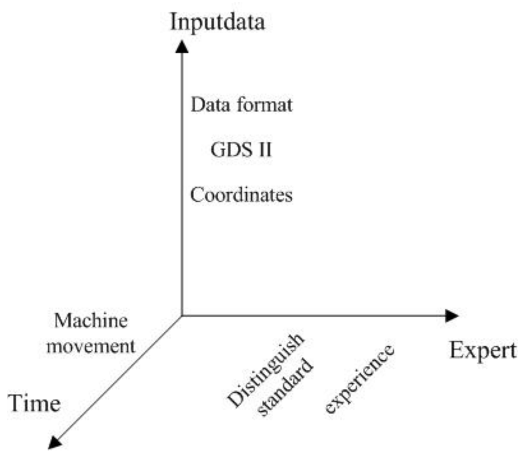

Figure2. The star net model in graphics

Figure2 describes every dimension could be the factors in our database warehouse. By checking those dimensions we could reduce the time required for data processing in our model [6]. We not only need the huge databases from Photomask company, but also need the expert to define the flaw in finished.

We process our database into data warehouse. When an expert distinguishes the MURA problems during the Photomask process, we will put input data into two different data categories which called database1 and database2. Further, we suggest database1 and database2 as our output data information (see Figure3). Therefore we could utilize the output data for a further coordinates. It makes them different from the original input data. By

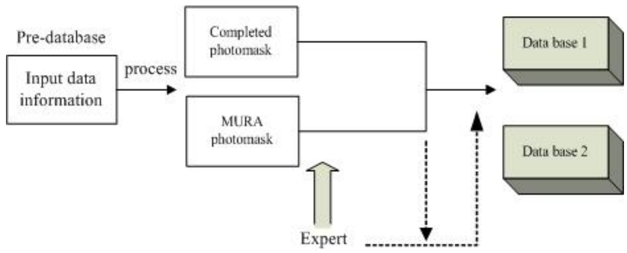

Figure3. The process of database

expert-select, we could use data mining techniques to find out the association rule inside this database in next.

B. Optimization mining

Our database would be processing by the expert, and we can make our pre-database an optimization. Figure4 describes when a graphic send to the laser writer machine, we have to collect all the Photomask layout information then get acquainted with the MURA problems in the produce.

This part of work is organizing the knowledge database and it depends on the expert which the chapter

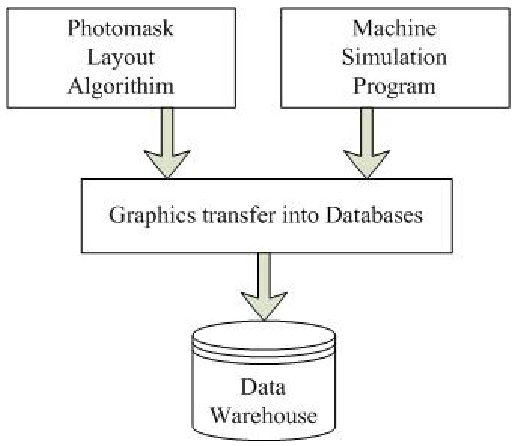

Figure4. The data warehouse process

two mentioned before. We also have to give the different definition between the input and output database and to make sure it could be the used database warehouse in the next plane (see Figure4).

Collecting all the data we need, we have to make sure the data were preprocessing which sort by expert at first, and change tables and spreadsheets to a data cube. Then computation the data cubes turn it into a data warehouse. After all of this, we could make the data mining application procedures.

III. THE MURA SIMULATION IN PHOTOMASK

The traditional data processing can not predict what kind of geometric would lead to MURA problems when a mask machine painted. And it is also due to the difficulties of data processing. Thronging Data Mining to predict the MURA modules, it could establish a set of feed-back system.

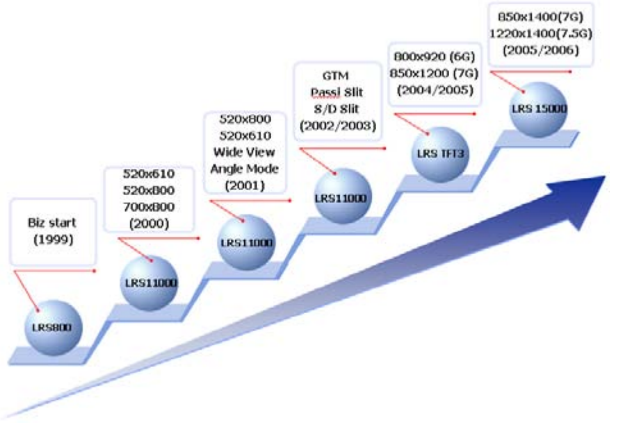

Figure5. The process of database

The MURA prediction module will be more accurate judgments than human experience. And because of its feed-back system, when the scheme run more and more over again, the database warehouse will not only become more precision but also adjust this module from its history database warehouse. The high level of FPD mask painted machine almost produced by Micronic Company. And the main differences in high-end machine specifications are the size of the mask depicted, and most specifications of the machines are the same (Figure5.) [3].

We will through the CATS program and PERL language to simulate the adjustment of the light exposure when the graphics depicted. This part of the graphics format will be converted into vector, and it could provide a database for our Data Mining scheme. By our scheme, when the MURA problems adjust at the plant, we can pre-know the risk value of MURA. With this module can provide a graphic adjuster a reference value, in order to get the best risk-adjusted of MURA.

This study is intended to find a model that fit for different machines and by using similar method to develop their own module of their own machine.

IV. The MURA Scheme

A. The procedures of MURA Scheme

The laser writer has lapped over each array graphics to build a larger area Photomask. The program has to compute the depicting of start point position, and output the overlap location plan.

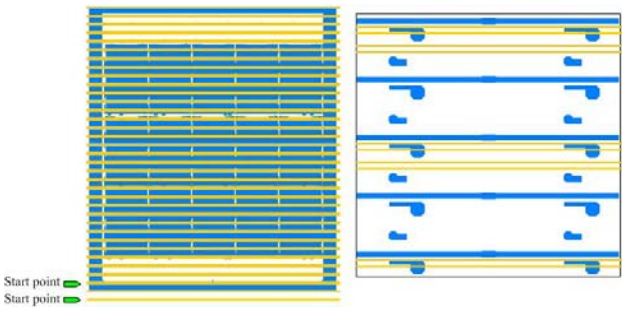

Figure6. The overlap of graphic

We try to simulate the same overlap graphics (Figure6.), because of no need for a Fracturing on the computing procession it should be faster than the original operation. If the first time adjustment of overlap will result of poor graphics, we can only restart the starting point position till it's qualify to best required. Since we do this step again, we will easily adjust the overlap in soon without the further fracturing for another once.

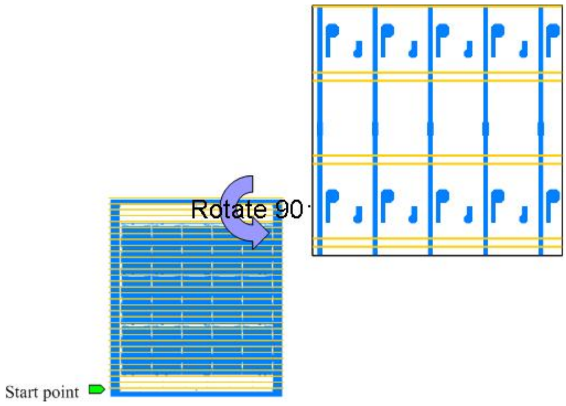

Figure7. Fracturing Rotated

When we get another new start point position, we can know the new overlap result and do not need to wait for the different redirection of mask layout (Figure7.). And it will save more time among 30 to 60 minutes to know the results.

After the simulated has been done, the all information will become our Data Mining database. We organized all the information from the standard operating of Photomask Layout, and transfer the Layout format into the program can read one.

The first part of our scheme is to shorten the adjustment time of MURA graphics and the output time of vector graphics in MURA adjustment. We will work through the CATS program and PERL language to simulate the adjustment of the light exposure when the graphics depicted. Because of this part, it will provide a good source of information to use in Data Mining which is composed in our second part.

The second part is combining the Data Mining Techniques into the MURA simulation. As a Photomask adjust at the plant, we can pre-know the risk value of MURA. It is involved in graphic analysis and graphic mining which we will discuss in next section. With this second port, it can provide a graphic adjuster a reference value, in order to get the best risk-adjusted of MURA.

B. The graphic Geometric of MURA Scheme

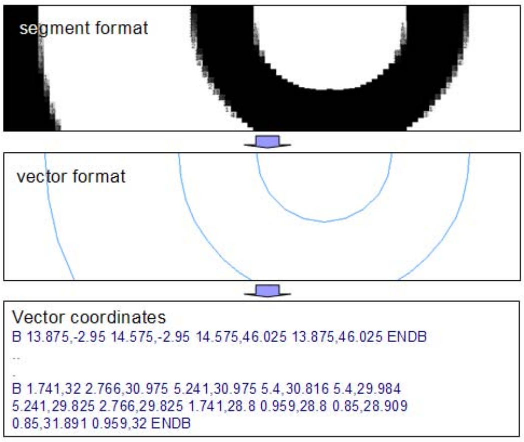

Figure8. The represent in MURA scheme

The Photomask file is one type of graphic geometric. And the graphic is hard to be quickly calculated in algorithm. To overcome this drawback, we make the point line represent the overlap region (Figure8.). Through the first part of a simulation study, we can gather the GDSII format when mask graphic exposure for the MURA adjustment at the plant. For its vector format, the available source of data mining could be established.

The laser painted machine’s pixel size is 0.25 um, address grid is 0.01 um, sweep length is 210 um, and CD Uniformity is 0.07 um. If the overlapping regional graphics are too complex, it is not only to control different laser energy in every pixel, but also necessary to control the good overlap of the exposure in the Y-axis precision regional at the plant.

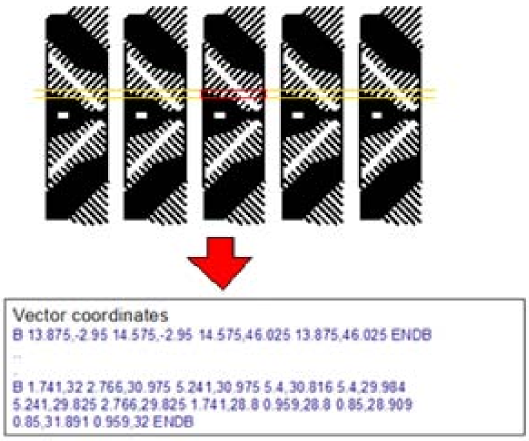

Figure9. The two lines show the overlapped region.

To identify overlap in this region of vector graphics, we have to analyze the overlapping coordinates region. From this information, we proposed to separate the regional grid within the 100-area ratio which is distributing the second part of the input data mining file (Figure9.). The general expectation is overlap on the simple geometric shapes region. But with the limit of graphic design, a mask usually unable placed over the region on the simple geometry panel.

V. THE MURA RISK RATING SYSTEM

In this section, we evaluate the MURA graphic in our scheme by a number of degrees. We named this part as a MURA Risk rating system in our scheme. We distribute the graphics into deferent degrees. This is the way we define the result of our output in Data Mining.

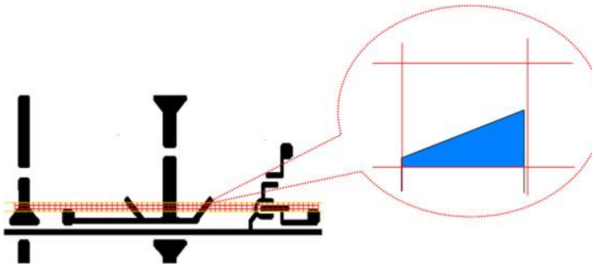

Figure10. The separated overlap area and The cut area of overlap

The bevel edge in overlap area is a highly-risk of MURA. In this study, we separate the overlap area into 100-area ratio (Figure10.). Then, we calculate the cut area of graphics. By analyzing the cut area of overlap, we could figure out the MURA related association rule in this scheme. According to the advantage of our feed-back system, the more information has been collected the more accurate of this system.

0~0.01	0.011~0.02	0.021~0.03	0.031~0.04	0.041~0.05	0.051~0.06	· · · · ·	0.971~0.98	0.981~0.99	0.991~1.0
0	1	1	1	0	0	· · · · ·	1	1	1

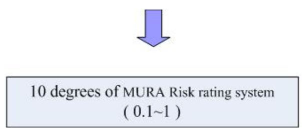

Figure11. MURA Risk rating system

We separate the overlap area into 100 species, and all the lattice point area can be calculate as ratio type. For example, the superficial measure of this lattice in fig8, the ratio is 0.35. It is settle down between 0.341~0.35 interval. When the calculated value is true, we take it as 1; on the contrary we take it as 0. And that make our importation become a MURA risk rating from 0.1 to 0.9(Figure11.).

This module is helpful for company to do the MURA risk management. If the risk level of MURA adjusted could be aware in advance. We may change the laser overlap start line to reduce the MURA problems which caused by the overlap area.

VI. THE MURA ANTICIPATION MODULE

A. The MURA prediction module based Neural Networks

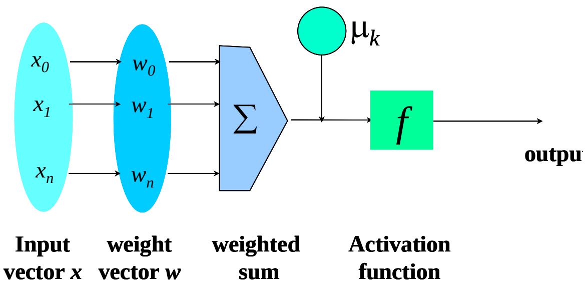

Figure12. A Neuron function mapping

There are already lots formations for a neuron analysis in mining association rules. Neural networks attempt to imitate a neuron in a human brain, with every link described as a processing unit. Neural networks learn from experience and are useful in detecting unknown connections between a set of input data and an output one. Like other approaches, neural networks detect patterns in data, generalize connections found in the data, and predict output ones. Neural networks have been especially noted for their ability to predict complex processes [7]. In order to tackle the MURA problems in our MURA scheme, we propose a reverse weighted sum to fit our MURA Risk Rating System.

Figure12 is an original Neural networks which explains the n-dimensional input vector x is mapped into variable y by means of the scalar product and a nonlinear function mapping. It is prediction accuracy generally high and output may be discrete, real-valued, or a vector of several discrete or real-valued attributes.

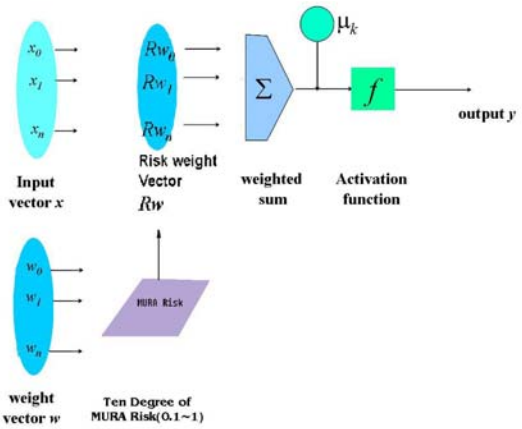

Figure13. A MURA Risk Basic Weight Vector RW

Lots of Neural network cases are weighted in the ratio of the heavier parts. Because of our MURA Risk Rating System is to determine by area, the small area and the strange area will increase the risk of MURA. According to our situation, the weight vector or the weighted sum there must be one will on the other hand. We made the vector w into vector Rw that reverse the ratio which could satisfy our schema requirement (Figure13.).

Processing elements or PEs are linked to inputs and outputs. The process of training a network involves diversifying the strength, or weight, of connections from the inputs to the output. Increase or decreases in the strength of a connection is based on its importance for producing the proper of the outcome. A connection's strength depends on a weight it receives during a trial-and-error process. That is the important part in out test to fix the weighted for fitting the behavior of MURA expert.

B. The MURA prediction module based Fuzzy Set

The traditional form of such an association rule is the implication

antecedent ⇒ consequent (c% confidence, s% support) (1)

Where the antecedent consists of one or more items in the transaction base being mined and the consequent consists of an item not in the antecedent [8]. Spatial data mining presents additional challenges not encountered in transaction data mining. Ordonez and Omiecinski [9] transform image data into traditional Boolean transactions, thus enabling the application of retail-style association rule-mining.

Fuzzy logic uses truth values between 0.0 and 1.0 to represent the degree of membership. The Attribute values are converted to fuzzy values. The classical fuzzy rule-based classifier consists of fuzzy rules that each describe one of the C classes. The rule antecedent defines the operating region of the rule in the n-dimensional feature space and the rule consequent is a crisp (non-fuzzy) class label from the {c1….. c} set:

$$r_i : \textbf{If } x_1 \text{ is } A_{i,1}(x_{1,k}) \textbf{ and } \ldots x_n \text{ is } A_{i,n}(x_{n,k}) \quad \textbf{then } \hat{y} = c_i, \; [w_i] \tag{2}$$

where A*i*,1…..A*i*,*n* are the antecedent fuzzy sets and *wi* is a certainty factor that represents the desired impact of the rule. The value of *wi* is usually chosen by the designer of the fuzzy system according to his or her belief in the accuracy of the rule [10].

The output of the classical fuzzy classifier is determined by the winner takes all strategy, i.e. the output is the class related to the consequent of the rule that has the highest degree of activation [10]:

$$\hat{y}_k = c_{i}^{*} \; , \; i^{*} = \arg \max_{1 \le i \le C} \beta_i(x_k) \tag{3}$$

These fuzzy rules providing us a way to another type that calculates in our MURA schema. This additional data selection steps in the KDD process. We will list the compare in the future. The boundaries between prediction and description are not clearly, but the distinction is useful for understanding the long-range discovery goal.

C. The Expectation of MURA

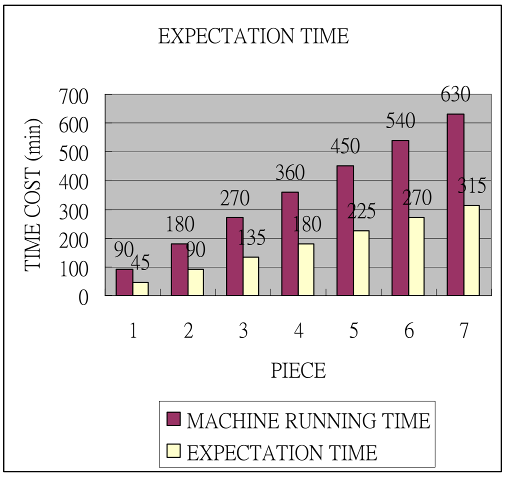

Figure14. Expectation Time Saver

As we have mentioned above, we know that the neural networks prediction accuracy is generally high; it works when training examples contain errors. But our goal is to save more than 50% of time when the laser machine acting in front of line. And our MURA risk rating system will also caused the result of the test time. The usually one piece of large Photomask laser modifying completed time is about 90 minutes (Figure14.). Our expectation to the MURA scheme is shorten the time while machine adjust to correct graphic, and reduce the MURA problems before the graphic send into render.

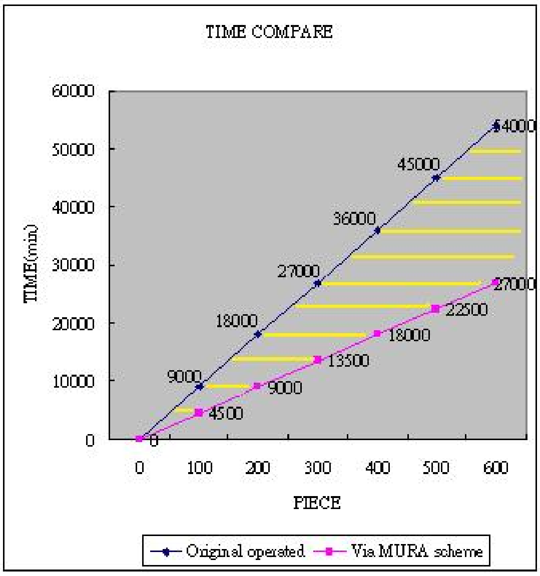

Figure15. The Compare of Time Cost

The figure15 shows how many time could be save when a Photomask machine standby in adjust the render graphic. We can tell from figure15 if each algorithm can make the database output value to be located at the horizontal line, this will be the rational range. Our propose is to find out the best and suitable algorithm that qualify to our MURA scheme, but it need more support from private enterprise.

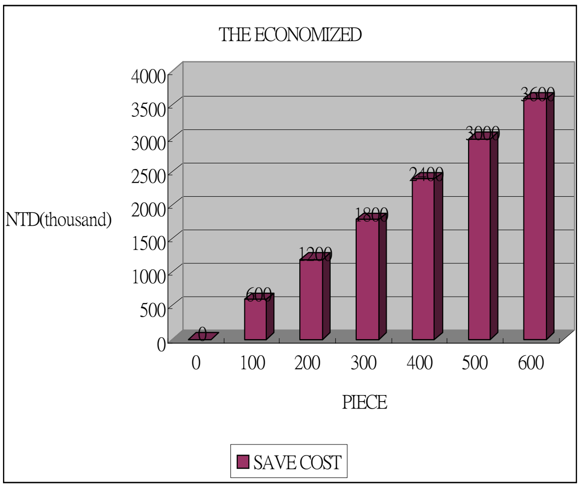

Figure16. The Economized via MURA scheme

Figure16 shows how the scheme economized in a company. To our research, it will waste about 8,000 NTD per hour when a Photomask machine is standby. And when a graphic adjust in stage it usually cost 90 minutes to wait for expert adjusted. If via our scheme, we can reduce about 50% time in graphic adjust. When two each Photomask is production, we will save 8,000NTD immediately. This means we can save 3,600,000 per year.

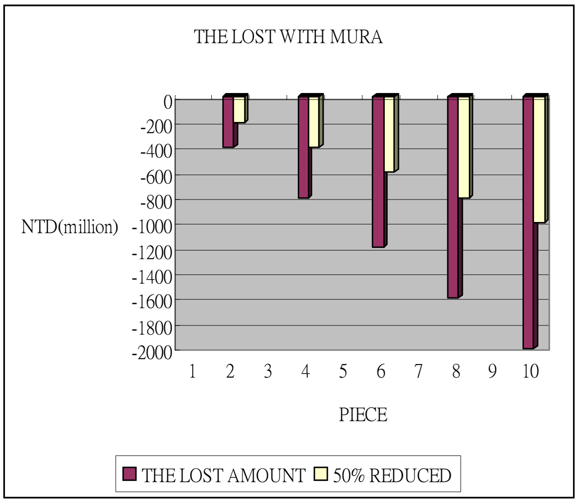

Figure17. The MURA Lost

Figure17 is about the loss of a Photomask company in MURA per year. According to our research, the Photomask company usually loss 20 million in MURA production. By using our MURA Risk System, it could help company reduce the damage in such a situation like this. If the MURA problems can reduce via our system, it could cut down the damage around 50 percent. It also means we can reduce the loss from 20 million to 10 million. The longer the system running the more precise the system is, and the more cost will be saved.

VII. CONCLUSIONS AND DISCUSSIONS

We have presented a novel framework in prediction of MURA problems. First, the MURA schema can help company to build their own database warehouse which is useful in the future. Then, the MURA Risk rating system also worked in avoid from the MURA in advanced.

It is indeed can saving time from standby machine, and expectation the Photomask processing graphic of MURA problems. We proposed a MURA scheme to solve the phenomenon of uneven brightness in display. By our scheme and MURA risk rating system, we can shorten the time and reduce the MURA problems. In the future, we need more input data to support our theory, and make our system more précised. And also the support from the reality company to participate in our model for calligraphy. By combine the data mining into MURA risk management, the MURA scheme can solve the un-brightness in display. And the collecting of expert database and optimization mining can help us gain an expert in ahead but also an expectation system. In the future, we need more input data to support our theory, and make our system more précised.

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