MANAGEMENT OF UNPLANNED CHANGES IN PRODUCTION PROCESSES: AI CONTROL SYSTEMS

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ABSTRACT

Quality risk management in industrial plants involves big calculations, the scale of which is often not only incomprehensible but also difficult to manage due to many parameters that affect the quality of production. Unsurprisingly, artificial intelligence-based quality management models are being introduced in manufacturing, only in niche, narrow areas, mostly for tracking product defects or identifying local quality defects. However, detecting the defect stage already is a late stage of the problem, which is almost always associated with a loss. Here comes the importance of prediction of problems or identifying of problematic patterns at an early stage before having production losses. Such attempts are rare and require a special approach. This type of module is needed for wide range problem forecasting in manufacturing. It should be configurable and clear not only by narrow area professionals, but also by medium-sized factory technologists who can configure such a system themselves to control their production quality risks. So here we are developing an approach whose strengths would be its simplicity, comprehensibility, fastness, and accessibility in its training, allowing us to understand why in one case or another the system predicts one decision or another.

KEYWORDS

IMS, ERP, production process management, planning optimization, AI planning

1. INTRODUCTION

Regarding the production planning, - the management of unplanned changes is critical for the stability of any production. Even though the original production plan, even if it is complex, is relatively simple to create, unexpected reproductions, or unforeseen shortcomings, disruptions or changes of equipment, personnel, or other resources make the original plan unworkable. It is often necessary to solve operational problems and redesign process or recreate poorly manufactured products. Adjustments to the plan and re-planning have a particularly high effect on costs. Therefore, the most important is not to have the hypothetical theoretical production plan of production, but the ability to predict production problems and adjust the plan to avoid re-planning and unforeseen changes. This comes via proper evaluation of production plan risks.

Although, it is not possible to predict all problems, but it is possible to learn from the past and analyze historical data, – process parameters by capturing the status of operations, states, events that affect unforeseen production changes that can influence the production plan. However, the amount of information does not allow a person to do this work. We need an intelligent system capable of performing such analysis by comparing different past situations and states with the current production situation, informing about possible disruptions and process problems or production defects before they occur or at an early stage, when it is still possible to avoid major production overhauls. It is always possible to reduce problems by preparing for them in advance and checking them. This is usually taken care of by the planning and quality department.

DOI: 10.5121/ijaia.2022.13407

However, it is expensive to waste resources in the quality department when inspecting each operation, but it is possible to inspect only operations that can cause biggest damage.

In the paper, we will generate such information using the artificial intelligence system SCANN that we will create and test on real production during this research. The system will help us understand of which workplaces, which processes and which events in production are more dangerous and riskier, and which are safer, less risky. To do this, it is first important to determine where the highest probability of damage lies during the planning of day-to-day operations. And then there can be different options, first - replan to avoid risky patterns, or give special instructions to the quality department that should receive on-time information about the operations on production and when those operations need additional inspection and what exactly they should check. In the paper we will make the system work in a screen-printing company (~100 employees, ~1000 production processes daily) where many different parameters are often encountered that require additional adjustment and calibration for each process, because each order involves a different layout, different colors, raw materials, and chemicals.

2. THE PRODUCTION DETAILS

We develop the system in the polygraphy company working with screen printing, tampography and offset-print technologies, performing over 1,000 operations per day. It was selected because of a suitable on production implemented ERP system that can be used during this development. The initial analysis of the main problems revealed three main reasons for the restructuring of production and the reproduction, which we will analyze in the study. The first problem taken into consideration, which causes the greatest damage, is the mistakes made by *employees* related to the process. The second problem is specific *product* related technological procedures repeatedly become problematic. The third problem is fluctuations or failures of the technical parameters of *workplace* equipment. These parameters can be tracked in the production management system by recording defects and problems. Collecting historical data and analyzing historical defect reports, assessing what damage has been done can give us a clue how to predict problems on production [2].

Our goal is to determine which operations are the riskiest in production, in the sense that there is a risk that the company will have unnecessary production losses [6]. Possible problem prediction and risk estimation system will try to predict:

- what employee can cause the reproduction or re-planning of production.
- what product related technology process can use more resources than average.
- what production line can create unnecessary unjustified losses of production.

This information will be used to plan the working day of the quality department. The risk management module SCANN developed in this paper will not replace people, however it will augment the skills of quality experts. It will allow to reduce employees number and dramatically increase their efficiency, enable them to get glimpse from historical company experience that they are unable to assess due to the scale of the information. SCANN algorithm will analyze 305265 operations of the last year. Since the information is heterogeneous, the process is determined by many criteria, such as technical parameters failures, operator errors, product related technology problems, and so on. SCANN system will give specific recommendations of the planning of production operation resources, SCANN will rate the operations on a scale of 0 to 1. Starting at 0 when the operation has no risk factors and ending at 1 when the operation is at maximum risk.

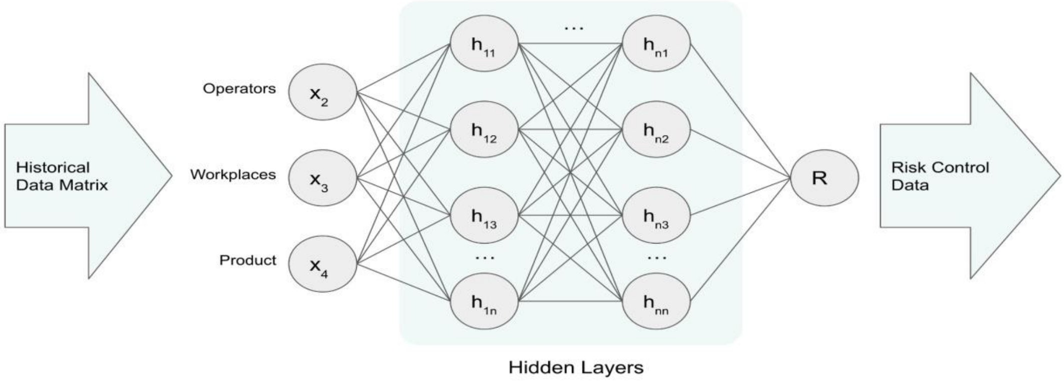
3. SCANN METHODOLOGY AND DEVELOPMENT

The development of SCANN uses some principles of FMEA (Failure mode and analysis), which has long been used in various fields [3]. In our case SCAN system will analyze the actual history large-scale data, predict future risks, and will help to manage them. We will evaluate the operations considering the information about production problems recorded by quality, production, technologists, and equipment maintenance specialists. The information is recorded in defect reports, which are used for training. The main feature is the possibility to "memorize" certain production patterns and models of the production, to identify which of them are risky, assess the degree of faultiness, identify dangerous combinations of circumstances of future production plans [5]. Also, it is important to plan production to avoid risky patterns or inform the responsible quality experts or operators. These can be problems related to inefficient production processes, the work of operators, products, production lines, etc.

We will use combinations of 3 aspects of production that combined in a non-optimal way can create damage or losses of resources. Employee (operator) work, products (technology issues), and production lines (workplaces). All the damage caused in the production are recorded in the defect reports, therefore it is possible to determine the extent of the damage, the circumstances of the product being produced at that time, the time when it was incurred and other relevant factors. Defect reports and accompanying information are taken as primary indicators to assess production risks. It is these indicators that the module will use to plan production less risky way and prepare recommendations for quality control procedures for a specific working day. In other words, we aim not only to abstractly evaluate the information, but also to take actions by replanning the production or preparing a quality control work schedule, where, when and what the quality controller must check in a specific workplace. The defect reports, represent the following information:

- Data
- Production
- Operation
- Operator
- Workplace
- Product
- Damaged raw materials
- The cause of the defect
- The magnitude of the damage

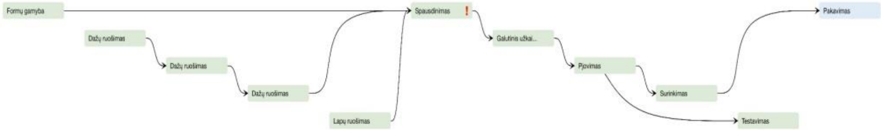
We will use the information about the company's activities stored on data servers accessible through the company's ERP system. In the ERP system, we will create a module called SCANN as an abbreviation of the Supervised Custom Artificial Neural Network, which will be evaluated using the primary information matrix [1]. During the “learning” process we will determine the weights of risk of employees which will give us a flexible possibility to assess the damage which could occur in certain state of conditions on production. We will set initial coefficients of 0, and during the learning system, the SCANN will “learn” these conditions evaluate it nodes and will allow us to assess the risk of future production plans [4]. We will evaluate 3 level networks with 3 incoming parameters: X1 product, X2 - operator, X3 - workplace,



Taking information about employees, jobs, and products from historical operations, we load the SCANN with historical information, which consists of 305265 events. By loading them through SCANN, we mark them as unproblematic. We then introduce the defect reports that we mark as problematic. SCANN php code:

```php
class SupervisedCustomArtificialNeuralNetwork
{
    protected array $weights = [];
    protected int $depth;

    public function __construct(?int $depth = 1) {
        $this->depth = $depth;
    }

    public function train($inputs, $targetSet): SupervisedCustomArtificialNeuralNetwork
    {
        foreach ($inputs as $key => $i) {
            for ($d = 1; $d <= $this->depth; $d++) {
                if (!isset($this->weights[$d][$i[0]][$i[$d]])) {
                    $this->weights[$d][$i[0]][$i[$d]][0] = $this->weights[$d][$i[0]][$i[$d]][1] = 0;
                }
                $targetSet[$key] === 1 ?
                    $this->weights[$d][$i[0]][$i[$d]][1]++ :
                    $this->weights[$d][$i[0]][$i[$d]][0]++;
            }
        }
        return $this;
    }

    public function predict($i): float
    {
        $weight = 0.0;
        for ($d = 1; $d <= $this->depth; $d++) {
            $weight += isset($this->weights[$d][$i[0]][$i[$d]][1], $this->weights[$d][$i[0]][$i[$d]][0]) ?
                $this->getWeight($i, $d) : 0;
        }

        return $weight;
    }

    private function getWeight($i, $d): float
    {
        if ($this->weights[$d][$i[0]][$i[$d]][1] === 0) { return 0.0; }

        return
            ($this->weights[$d][$i[0]][$i[$d]][0] === 0 ?
                1 :
                $this->weights[$d][$i[0]][$i[$d]][1] / $this->weights[$d][$i[0]][$i[$d]][0])
            / $this->depth;
    }
```

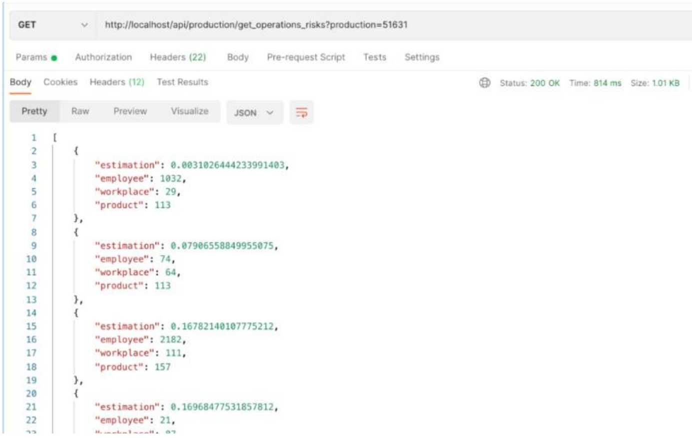
After evaluating planned future production operations based on historical operations and defect reports by assessing which operations are risky, we can show them next to the operation indicator. In the company's ERP system, we will mark an operation that exceeds the 0.3 limit with an exclamation point "!".



However, this company where the system of defect reports is implemented, is in the starting stages of the implementing of the automated module and still has not collected enough historical information for a deeper report or analysis. Although the first indicators are already visible, there are still no patterns, which are the most important for us in this study. So, we take 45 sample events to simulate it, which are prepared to show the desired trends. We will mark them as "defective" as if they have historically caused damage to the company.

```
private function evaluateWithCANN(Production $production): array
{
    $inputs = [];
    $desired_output = [];
    $response = [];
    $sampleData = [[1032,29,113], [74,64,113], [2182,111,157], [21,87,157], [920,87,157], [68,87,157], [2230,29,117]
    $sampleScore = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,


    foreach ($this->getLastYearBookings() as $booking) {
        if ($booking['employee_id'] && $booking['workplace_id']) {
            $inputs[] = [$booking['employee_id'], $booking['workplace_id'], $booking['product_id']];
            $desired_output[] = 0;
        }
    }

    foreach ($this->getLastYearDefects() as $defectAct) {
        if ($defectAct['employee_id'] && $defectAct['workplace_id']) {
            $inputs[] = [$defectAct['employee_id'], $defectAct['workplace_id'], $defectAct['product_id']];
            $desired_output[] = 1;
        }
    }

    $inputs = array_merge($inputs, $sampleData);
    $desired_output = array_merge($desired_output, $sampleScore);

    $CANN = (new SupervisedCustomArtificialNeuralNetwork(2))->train($inputs, $desired_output);

    foreach ($sampleData as $key => $input) { //Sample with the sample data to get more intensive defect patterns
        $response[$key]['estimation'] = $CANN->predict($input);
        $response[$key]['employee'] = $input[0];
        $response[$key]['workplace'] = $input[1];
        $response[$key]['product'] = $input[2];
    }

    return $response;
}
```

After testing the system with test data, we get the following results:



The results (all of which are detailed in the appendix: “Results”) show that employees who were entered in the test data as having defective reports, such as ID: 74. It is clear now, that when employee ID: 438, working at workplace ID: 111, the risk of the operation rises to 0.334…. However, when the same worker works in workplace ID: 107, the degree of risk drops to 0.0485…, which is considered risk-free. The SCANN system makes this decision by "seeing" that the employee has not had any problems working at this workplace many times before, but this same employee has problems when he is working on another working place or with another product. This can be caused by the lack of competence or qualification that SCANN can urge to solve.

The development of the model helps for the company to evaluate large amounts of data in a very short time and to have the evaluation information almost instantaneous. The system ran on a server with 8 cores and 32 RAMs. All the training and evaluation with test data (305265 production historical events and 45 sample evaluation data) was performed in 851ms, i.e., less than one second. This speed is sufficient to use the assessment live when needed to assess the production procedures for future production plans in a specific situation.

4. Conclusion

1. Production risk assessment using the SCANN system opens a new perspective for the risk assessment of the production management. The risk assessment module needs a half of a year of work analysis after launched for gathered of sufficient information, to create a full-fledged neural network knowledge module, which allows controlling the company in a very effective way.

2. The new mode of the automatic planning of the company's work can be adjusted to plan production, to analyze the alternatives, and create the plan of minimum risk factors, where the characteristics of all operators and production lines and products related technological issues are combined in such a way as to achieve the highest optimal level historically achieved in the company.

3. Automatic planning optimization allows the most efficient use of the competencies of operators and the strengths of production lines, the compatibility of products with different processes, which is not possible by any logical deduction or human experience-based decisions.

4. The resources of the quality department are optimized so that the focus of the work is on the main problems instead of checking everything in a row, as there is no point in checking operations where there is a historically very low or zero rate of problems or damage. Adjusting quality procedures and focus also reduces the resources required for quality control.

5. The SCANN system creates a knowledge network that goes beyond a person's knowledge of the risks of a company's operations and shapes the work of the R&D department in a completely different way. Here, the tasks that are most risky will come to the fore. The development, research, and problem-solving department in a company begins to work with risk mitigation rather than tasks that may be subjective or result from seeing and understanding only a partial picture of the company's operations. This approach helps departments to unify the production-wide knowledge system.

6. The SCANN system provides opportunities to assess workplace risk separately, for example by addressing future investments in new equipment. The risk criteria for different machines can be momentarily evaluated, considering not only the speed and price criteria of the equipment, but also the damage and risk factors it causes.

7. The SCANN system allows individual risk assessment of employees to compare them with each other, assessing the need to improve competencies and qualifications. It can be used as a strong motivation system to achieve higher production safety by working with risk criteria for production sites created by specific operators.

5. RESULTS

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