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Optimum Selection of Information Terminals for Production Monitoring in Manufacturing Industries

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The purpose of automated acquisition of production data in manufacturing industries is aimed to provide accurate data about the performance of the scheduled tasks and the production process. Hence, easier and more effective production control can be achieved. The information acquired includes the duration of each operation, the number of manufactured items of products, the amount of scrap as well as the duration of downtimes and their root-causes. A way to acquire relevant data makes use of special-purpose information terminals. The problem that arises here is how to select the optimum number of the terminals in order to minimize the overall losses. The approach presented below relies on optimization of a stochastic criterion function, which combines the terminal costs and costs related to the waiting times during busy sessions. The solution suggested is based on using the distribution of events, recorded during the past production session. A case study dealing with optimum selection of terminals in a real production process is presented in detail.

Keywords: production systems, optimization, production monitoring, production control

0 INTRODUCTION

More and more manufacturing companies are introducing multi-information terminals (MIT) in order to allow peer monitoring of the production process. These systems complement business information systems, such as ERP's (Enterprise Resource Planning). There are many ways in which relevant production data can be collected [1] and [2]:

- entirely manually by filling up special forms,
- automatically from the machines,
- on demand and on-line through special purpose terminals.

Data of considerable relevance for the production process encompass the following items: execution times needed to complete an operation from the work order, number of manufactured parts, the amount of scrap parts and duration as well as root-causes for downtimes.

In order to assure best quality data, events are recorded at the time and the site of their origin. According to [3], the quality of information is measured by accessibility, accuracy, timeliness, integrity, density, suitability, understandability, and objectivity.

Specially tailored information terminals represent a convenient means to record the production events (Fig. 1). Different technologies for data entry can be employed, however the most frequent one is the bar code [5]. Bar code is also widely used with different working sheets and personal identification cards.

Fig. 1. *A terminal used to record production events (manufactured by Kolektor Sinabit Ltd.)*

Prior to implementing the terminals in the production process, the following issues have to be considered:

- distribution of events, typical for the underlying production process,
- duration of events,
- distances between working places and terminals,

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- terminals cost, including costs for installation and maintenance.

Terminal costs can be reduced by cutting the number of terminals. However, new costs are introduced because of idle times workers have to spend while waiting for a free terminal. Hence, our problem is to find the optimum number of terminals, which minimizes the *overall* costs.

The paper is organized as follows. In the first section the problem of optimum selection of terminals is stated in the form of a stochastic optimization problem. Basically, the idea is to employ a record of production events from the production history. The second section describes a simple procedure for solving the optimization problem by means of simulation. The third section reports on results, obtained in a real production plant.

1 PROBLEM STATEMENT

Organization of the manufacturing process

Let us first shortly outline the organization of a production process in a typical manufacturing industry.

The basic item is *work order*, the result of which are manufactured products. Work order is usually divided into many discrete operations defined by the technological procedure. Each worker is responsible for his/her own *workplace* and for handling *operations* assigned to it. A workplace consists of one or more machines, which are capable of executing the specified operations.

In order to get clear insight into the production efficiency, the following events have to be recorded [4]:

- start of each operation,
- end of work,
- start of a downtime,
- end of a downtime.

The origin of waiting times

At each registration, e.g. at the start of work, the operator has to enter data about who will perform the operation (personal number), the allocation of operation (machine number) and the code of operation along with the underlying work order. When a downtime has to be registered, the worker has to enter additional data regarding the root cause for it. Downtime code can be found on a printed bar-code list. The registration procedure is depicted in Figure 2.

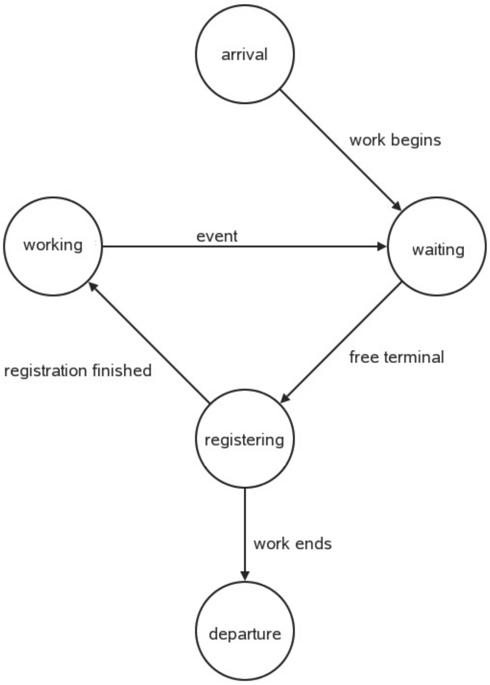

Fig. 2. *Particular stages in the event registration procedure and emergence of the waiting times*

In order to *register* an event, one has to access the terminal and enter the relevant data. Provided the terminal is busy, one has to wait in a queue. In this paper it is assumed that any of the available terminals can be freely selected. Time needed to access the terminal is neglected.

In principle, waiting times could be entirely eliminated by installing sufficiently many terminals. However, such a solution is not an optimum one since by raising the number of terminals their costs increase monotonicaly. Therefore, we have to choose a criterion function that will include both types of costs.

Criterion function

Let N be the number of terminals and $J_{cost}(N)$ their cost normalized per day. This cost is calculated according to the amortization period of 4 years. The annual cost implied by a terminal is thus a sum of amortization costs and maintenance costs. The former and the latter are as high as one quarter and one tenth of the purchasing price respectively.

Let $J_w(N)$ represent daily costs due to the waiting times. This can be simply expressed as

$$J_w = c_w \tau(N) \quad (1),$$

where c_w represents labour cost per employee and $\tau(N)$ stays for daily accumulated waiting time.

Comment 1

The time required to enter the data in the terminal is about 30 secs and this is not considered as loss caused by waiting.

Comment 2

The accumulated daily waiting time $\tau(N)$ is random variable with a probability density function $p(\tau(N))$ defined on the open interval $[0,\infty)$. Its analytical expression is not known.

Because of the dispersion in waiting times, we are looking for such a τ_α, that the probability $P(\tau \leq \tau_\alpha)$ equals 1-α. Here $0 \leq \alpha \leq 1$ is the degree of significance. For example, when $\alpha=0.05$ there is 95% probability that the waiting time at the given number of terminals N will be $\tau(N) \leq \tau_{0.05}(N)$ [6].

The following stochastic optimization problem should be solved in order to find the optimum number of terminals:

$$N^* = \arg\min_{N \geq 1} \left(J_{cost}(N) + c_w \tau_\alpha (N) \right) \quad (2).$$

Comment 3

Because of the strictly monotonically increasing function $J_{cost}(N)$ on the right side of (2) and strictly monotonically decreasing function $\tau_\alpha(N)$, the criterion function (2) is unimodal. In that case, there exists N^*, such that the criterion function reaches its minimum.

2 SOLVING THE OPTIMIZATION PROBLEM

To solve the problem (2), the knowledge of event distribution is required. The frequency of events differs during the working day, depending on the type of production. In order to estimate the daily profile of the density of events, some recorded realization of events is needed. These data are referred to as the *learning data set*.

Preparation of the learning data set

The acquisition of learning data is done by means of the *currently available* acquisition system. This can be purely manual in some cases. In other cases process history or diverse information sources can be utilized. Each recorded event carries information about the start and the end of an activity. Accuracy of the learning data is of considerable importance here so that problems might occur in cases where data resolution is poor. For example, manually entered data are rounded to a half an hour or an hour instead of a second or minute. A typical consequence of rounding can be seen in higher density of events around full hours, which results in higher values of the estimated waiting times.

Calculation of waiting times on the learning set

Each event is associated a time stamp, i.e. the date and time of its occurrence. The algorithm for calculation of waiting times is executed within 5 steps:

1. find the terminal, which will first become available;
2. estimate the time a terminal will become available (if terminal is already free, registration can start immediately);
3. waiting time is calculated as the difference between the time of availability of the terminal and the occurrence of the event;
4. waiting time is extended with time required for data entry;
5. calculated waiting time in step 3 is added to the daily accummulated waiting time.

The algorithm results in a sequence of waiting times:

$$T = \{\tau_1,...,\tau_M\} \quad (3),$$

calculated for each day separately. The complexity of the algorithm is $O(m*N_{max})$, where m is the number of events in the learning set and N_{max} is the highest assumed number of terminals.

Figure 3 illustrates a simple case in which waiting times for one and two terminals are calculated respectively. In both cases there are three events, which occur at times 2, 7 and 13. Every event is 7 time units long. The first event, which occurs at time 2, is immediately processed in both cases. The same happens with events 2 and 3 in the case of two terminals. In the case of one terminal, the first event is still being processed when the second appears at time 7. In the same manner the second event is still being processed when the third one occurs at time 13. Therefore, handling of the last two events has to be delayed

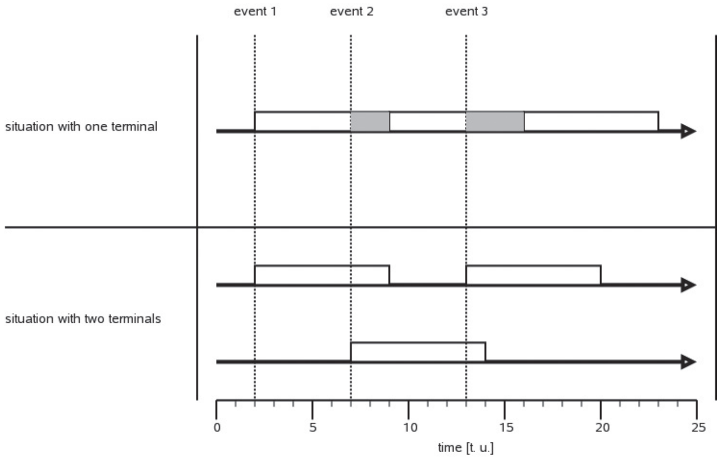

Fig. 3. *Illustrated calculation of waiting times*

from time 7 to time 9 for the second and from time 13 to time 16 for the third event. The diagram shows waiting times in gray color. To sum up, in the situation with two terminals there is no waiting time while in the situation with one terminal, the waiting time equals 5 units.

Determination of the critical waiting times

In order to approximate the probability density function of the random variable τ_d one can calculate the histogram derived from the set T (see Eq. (3)). The distribution function varies with respect to the number of terminals and its shape is hard to define analytically.

Optimization method

Let's first notice that the argument of the criterion function (2) is integer. In this case we deal with the one-dimensional problem, which is relatively simple. Given the fact that the expected optimum number of terminals is not high, we apply a simple optimum seeking procedure, which reads as follows:

$N_{opt} = 0$, $J_{opt} = 1e10$
for $N = 1$ to N_{max} do begin
calculate the histogram of waiting times for N terminals
calculate the critical waiting time τ_α
calculate the criterion function $J(N)$
if $J(N) < J_{opt}$ do begin
$N_{opt} = N$
$J_{opt} = J(N)$
end
end

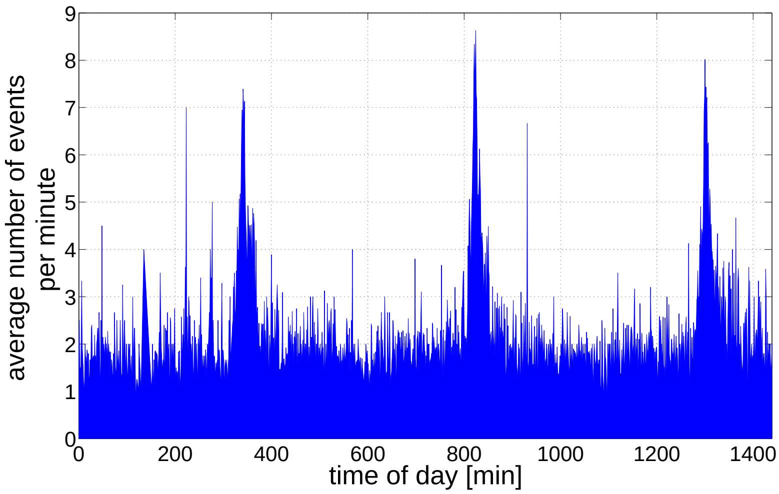

Fig. 4. *The average number of events per minute during the day. Peaks at 6 am, 2 pm an 10 pm coincide with the shift changes.*

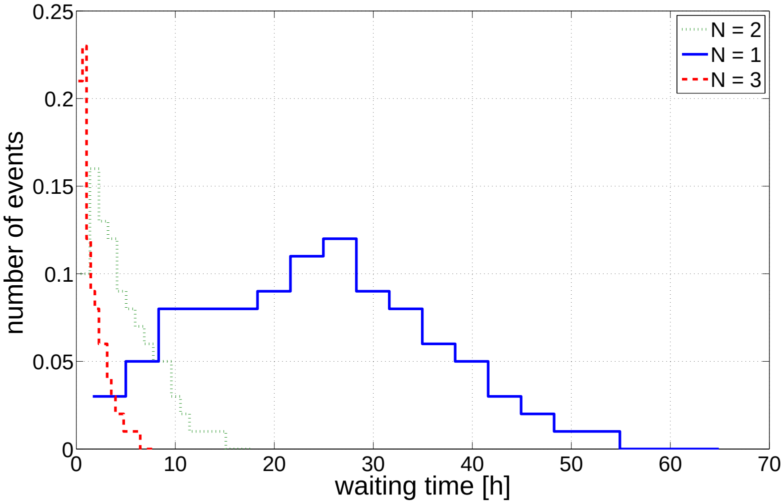

Fig. 5. *Histograms of waiting times for various numbers of terminals. When increasing the number of terminals, critical expected time approaches zero.*

3 CASE STUDY

The approach above has been applied in a case study related to the manufacturing industry. The underlying production line employs 60 workers in the morning and afternoon shift. Figure 4 presents the frequency of events recorded on the daily basis.

The learning set includes 1205 working days. We have collected 331448 events during this time period. Cost parameters c_w=4.6 and c_0=1500[1] were applied in the optimization procedure.

During the optimum search, a new histogram is calculated for each newly selected number of terminals. Figure 5 shows histograms for *N*=1, 2, 3. The critical expected time $\tau_\alpha(N)$ approaches zero with the raising number of terminals.

Figure 6 shows the values of the criterion function (2) in dependence of the number of terminals.

Figure 7 shows the way the optimum *N** varies with respect to the parameter α. When increasing α, the optimum number of terminals decreases. This could be explained by the fact that increased α leads to the overoptimistic (too short) waiting times. The recommended value is α=0.05.

4 DISCUSSION

The results deserve some comments:

1. The proposed solution depends very much on the quality of the learning data set. Special attention has to be paid to that issue. Namely, incorrect time stamps, associated with the recorded events, do not reflect the actual state of the production process.
2. Surprisingly, the solution presented in this case study turns to be very similar to the heuristic solution applied so far in practice. The rule of thumb being used suggests one terminal for 10 to 15 workers, depending on the size of the plant.
3. Our solution provides clear insight into the expected costs due to the waiting times conditioned with the number of terminals. Moreover, Figure 6 is helpful in figuring out the cost of additional redundancy. More precisely, though the optimum is reached for *N**=5, additional costs to install one or even 2 more terminals are almost negligible. However, the overall system s much more robust in case that one or more terminals fail to operate properly.
4. In this stage we did not take into consideration the site distribution of the terminals. Instead, we were only searching for the optimum number of them assuming that the terminals are distributed uniformly along the production plant and the paths between work places and the terminals do not differ much.

5 CONCLUSION

In this paper the problem of optimum terminal arrangement in the production plant is

[1] The units are intentionally omitted.

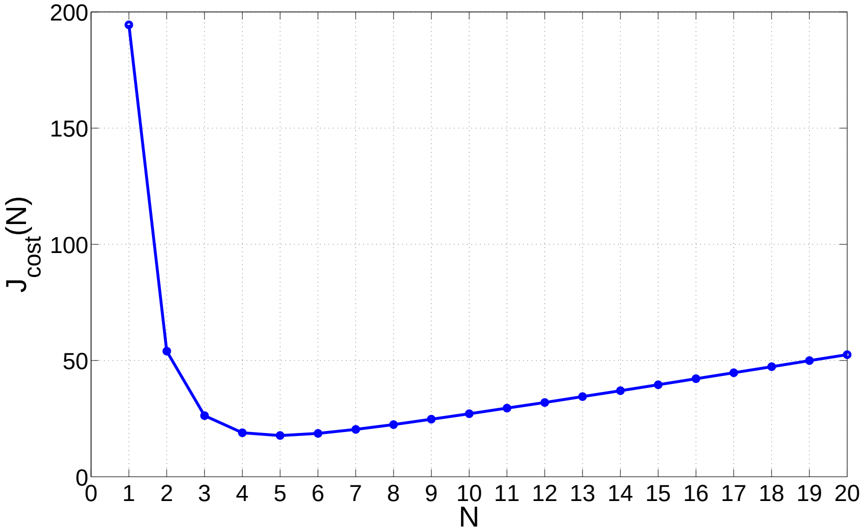

Fig. 6. *Criterion function J_{cost}, for a given critical value α=0.05, shown as a function of the number of terminals N. The lowest value of 17,73 is reached at N = 5.*

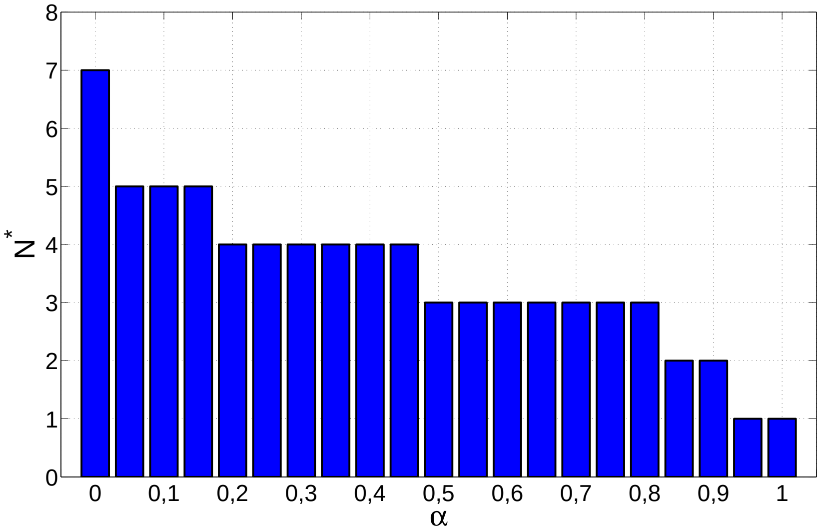

Fig. 7. *Dependence of the optimum number of terminals from the parameter $\alpha \in [0,1]$*

addressed. The problem has been formulated as optimisation of a stochastic criterion function. Main goal of this study was to develop the algorithm for determination of the optimum number of terminals in the manufacturing industries. The proposed criterion function takes into account two types of costs: those due to the waiting times and those caused by the installation of the terminals. One possible upgrade of the presented solution would also consider the geographical dimension of the problem. Namely, it is not possible to install a terminal at any site in the production plant. Availability of power and communication outlets should also be considered. Possible upgrade should concern the application of the information terminals, though they are more expensive than the traditional ones.

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