OPTIMAL SELECTION OF INFORMATION TERMINALS FOR DATA ACQUISITION IN MANUFACTURING PROCESSES

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Abstract

Information terminals are devices used in manufacturing industries for registering relevant events such as start and end of operations, emergence of a fault or breakdown, the amount of manufactured items as well as the amount of scrap. The data collected by the terminals serve to fully monitor the manufacturing process. In addition, data are archived in the business information system thus allowing the overview on system performance and costs. The problem treated in this paper is to select the optimal number of the terminals needed to accommodate the needs of a manufacturing process. This implies minimization of a cost function which combines investment costs and eventual losses caused by waiting times during busy sessions. The events that have to be registered appear at random times. To simulate the performance of a certain number of installed terminals a suitably long realization of random events is needed. Without terminals, the events acquisition can be done only by hands, which not only takes effort but is also vulnerable to erratic entries. In order to avoid manual acquisition of long events records we propose to use the model of random events.The solution we suggest employs prior distribution of events recorded during the production process. This information is then used for estimation of the probability density function (pdf) of time intervals between two consecutive events. The pdf, in turn, serves for generating statistically significant number of realizations of events records (Monte Carlo simulation) that provide the distribution of waiting times under various configurations of information terminals. A case study dealing with optimal selection of terminals in a real production process is presented in detail.

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

Presenting Author's Biography

Jani Kleindienst graduated in computer science, Faculty of Computer and Information Science, University of Ljubljana, in 2000 and completed his MSc. degree in information managemet at the Faculty of Economics in 2004. Since 2000 he has been affiliated with company Synatec, serving as software developer, project manager and chief software architect. He has been involved in the design and development of information systems for on-line production monitoring. He is now employed as a R&D project manager in a newly founded company Kolektor Sinabit and PhD student at the Jožef Stefan International Postgraduate School.

ISBN 978-3-901608-32-2

1 Introduction

In order to effectivly supervise the production processes in manufacturing industries, it is important to have accurate data about the execution of the scheduled tasks, condition of equipment and quality of the product. The duration of operations, the number of manufactured items of products, the amount of scrap, as well as the duration of breakdowns along with root-causes are just few examples of data that have to be collected and stored for further analysis [1].

Data can be acquired in two ways [1],[2]:

- automatically from machines making part of the manufacturing process,
- on-line through special purpose information terminals used on demand by workers (sometimes referred to as "industrial touch panel computers", c.f. Noax, [3]).

In the first case, a machine directly delivers data to the business information system, while in the second case it is the worker who provides data by typing and using bar-code reader. For example, prior to start with a new operation the worker has to provide data such as his personal ID number, machine ID number and the code of operation along with the underlying work order. On the other hand, in case a downtime occurs, worker in charge has to enter event description and additional data regarding the root-cause for it. Downtime codes can be found on a printed bar-code list.

Fig. 1 Example of information terminal (manufactured by Synatec).

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

In principle, waiting times could be entirely eliminated by installing high enough number of terminals. However, such a solution is not optimal. Namely, by raising the number of terminals costs rise monotonically. Therefore we have to choose a criterion function that will include both types of costs.

This paper focuses on the problem of selecting a suitable number of terminals in order to balance costs and benefits in some optimal way. In the second section the problem of optimal selection of terminals is stated in the form of a stochastic optimization problem. The background idea is to employ the distribution of production events from the production history. The third section describes a simple procedure for solving optimization problem by means of simulation. The fourth section reports on results obtained on a real production plant.

2 Problem statement

2.1 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 the sum of amortization costs and maintenance costs. The former and the latter equal to one fourth and to one tenth of the purchasing price respectively.

Let $J_w(N)$ represent daily costs due to the waiting times and are calculated by

$$J_w = c_w \tau(n \mid N) \tag{1}$$

where c_w presents labour cost per employee and $\tau(n \mid N)$ stays for accumulated waiting time during the n^{th} day. Note that τ is conditioned by the number of terminals N.

Comment 1
The time required to enter the data to the terminal is about 30s and this is not considered as loss caused by waiting. ∇

Comment 2
Accumulated daily waiting time $\tau(n \mid N)$ is random variable with a probability density function $p(\tau(n \mid N))$ defined on the open interval [0,∞). Its analytical expression is not known. ∇

Because of the dispersion in waiting times, we are looking for such a τ_α, that the probability $P(\tau \le \tau_\alpha)$ equals

$$P(\tau \le \tau_\alpha) = 1 - \alpha, \quad 0 \le \alpha \le 1$$

Here α is the degree of significance. For example, when α = 0.05 there is 95% probability that the waiting time at the given number of terminals N will be $\tau(N) \le \tau_{0.05}(N)$ [4].

Hence we arrive to the stochastic optimization problem that should be solved in order to find the optimal number of terminals:

$$N^*(\alpha) = \underset{N \ge 1}{argmin} \left(J_{cost}(N) + c_w \tau_\alpha(N)\right) \tag{2}$$

Comment 3
The optimal number of terminals N^* depends on the degree of significance α. So, if we want to accommodate the extreme situations (i.e. less probable realizations of waiting times), we have to apply smaller α. This indicates less risk in the expected performance. ∇

Comment 4
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, such a N that the criterion function reaches its minimum. ∇

3 Solving the optimization problem

In order to be able to solve the optimization problem it is necessary to know the distribution of events during the day. Accumulated waiting time $\tau(n|N)$ at day n, provided N terminals are available, depends on the number of events and their occurrence times. Accumulated waiting time can be calculated only by means of simulation (to be explained later). Moreover, the waiting times differ from day to day in a random manner and the distribution of their values can take any form. Therefore, we cannot assume in advance any parametrization of the pdf $p(\tau(n|N))$. Instead we approximate it by a histogram of $\tau(n|N)$. In order to do that n_D should be chosen high enough.

3.1 Calculation of waiting times on a set of events

Let us assume for the moment we have a set of events over a long enough period of process operating time (say n_D days). Let the k^{th} event, that happened on the n^{th} day, be associated the time stamp $t_{n,k}$ thus resulting in a set

$$\begin{aligned} T(n_D) = \{&t_{1,1}, t_{1,2}, ..., t_{1,K_1}, \\ &t_{2,1}, ..., t_{2,K_2}, ... \\ &t_{n_D,1}, ..., t_{n_D,K_{n_D}}\} \end{aligned} \tag{3}$$

The algorithm for calculation of daily waiting times is executed within the 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 accumulated waiting time.

The algorithm results in a sequence of waiting times $T = \{\tau(1|N), \ldots, \tau(n_D|N)\}$, calculated for each day separately. The complexity of the algorithm is $O(m \cdot N_{max})$, where m is number of events in the learning set and N_{max} is the highest assumed number of terminals.

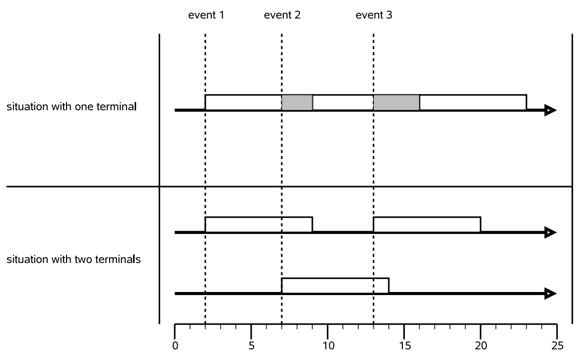

Fig. 2 Illustrated calculation of waiting times.

Fig. 2. 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 requires 7 time units for the data entry into the terminal. The first event, which occurs at time 2, is immediately processed in both cases. The same happens in the case with the remaining of the events in the situation with two terminals. On the other hand, in case with 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 from time 7 to time 9 for the first event and from time 13 to time 16 for the second event. The diagram shows waiting times in gray color. To sum up, in the situation with two terminals there is no waiting time and in situation with one terminal, waiting time equals 5 units.

3.2 Determination of the critical waiting times

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

Although $\tau(N)$ is the sum of single waiting times $\tau(1|N), \ldots, \tau(n_D|N)$, calculated over days $1, 2, 3 \ldots, n_D$ it is almost impossible to analytically determine the connection between $p(\tau(d|N))$ and $p(\tau(N))$.

In order to determine the τ_α distribution of $p(\tau(N))$, we bring into use the central limit theorem [4], which states:

Theorem. Let x_1, x_2, ..., x_r be independent random variables with equal distribution, mean value μ and variance σ^2. Let be

$$S_r = \frac{\sum_{i=1}^{r} x_i}{r} \tag{4}$$

then

$$Z_r = \frac{\sqrt{r}\,(S_r - \mu)}{\sigma} \tag{5}$$

converges in distribution to the normal distribution $N(0,1)$. ∇

In other words, limit ratio Z_r is asymptotically normally distributed with zero mean and unit variance.

In the context of our problem, we focus on the sum

$$\tau(N) = \sum_{i=1}^{n_D} \tau(i|N) \tag{6}$$

of randomly distributed $\tau(i|N)$ with mean value μ and variance σ^2. Therefore, the standard sum

$$Z(n_D) = \frac{\tau(N) - n_D \cdot \hat{\mu}}{\sqrt{n_D} \cdot \hat{\sigma}} \tag{7}$$

is also normally distributed with mean value 0 and variance 1. We know the critical value of Z_α

$$P(Z \leq Z_\alpha) = \alpha \tag{8}$$

from the table of critical values for normal distribution. Accordingly, the critical value of $\tau(N)$ reads

$$\tau(N) = \frac{Z_\alpha \sqrt{n_D}\hat{\sigma} + n_D \cdot \hat{\mu}}{\tau(N)} \tag{9}$$

where

$$\begin{aligned} \hat{\mu} &= \frac{\tau(N)}{n_D} \\ \hat{\sigma}^2 &= \frac{1}{n_D - 1} \sum_{i=1}^{n_D} (\tau(i \mid N) - \hat{\mu})^2 \end{aligned}$$

3.3 Optimization method

The optimization procedure is actually trivial. Let us first notice that the argument of the criterion function (2) is element of the set of integer numbers. In our case we have to deal with one-dimensional problem, which is relatively simple. Given the fact that the expected optimal 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 histogram of waiting times for N terminals
calculate critical waiting time τ_α
calculate criterion function $J(N)$
if $J(N) < J_{opt}$ **then begin**
$N_{opt} = N$
$J_{opt} = J(N)$
end
end

3.4 Estimation of the daily distribution of events

Getting long data sets can be costly if done ”by hand”, that is, before the terminals are installed. Therefore it is realistic to assume that prior data consists of a set of daily records over a restricted period of operation of n_{OP} days ($n_{OP} \ll n_D$).

Let us first notice that the density of events is not constant but is changing during the day (c.f. Fig.3). It is assumed that the profile depends on the nature of the manufacturing process, e.g. it differs for mass production compared to the workshop production. The interval between two events occurring at times t_i and t_{i+1} is random variable and is assumed to have exponential distribution

$$p(\Delta t \mid \lambda(t)) = \lambda(t) e^{-\lambda(t)\Delta t} \tag{10}$$

where $\Delta t = t_{i+1} - t_i$ and $\lambda(t)$ denotes the time-varying parameter of the distribution.

In order to simplify the problem, we approximate the daily profile of $\lambda(t)$ by a piecewise function $\lambda(t) = \lambda_i$, $t^*_{i-1} \leq t \leq t^*_i, i = 1, ..., \nu$. The daily profile is assumed to be the same from day to day.

Now, given the prior data

$$\begin{aligned} D_{n_{OP}} = \{&t_{1,1}, t_{1,2}, ..., t_{1,K_1}, t_{2,1}, \\ &..., t_{2,K_2}, ...t_{n_{OP},1}, ..., t_{n_{OP},K_{n_{OP}}}\} \end{aligned}$$

one has to find the probability density function $p(\lambda_i \mid D_{n_{OP}})$. It can be shown [5] that the maximum likelihood estimate reads as follows

$$\hat{\lambda}_i = \frac{k}{\sum_{j=1}^{k} x_j} \tag{11}$$

where $x_j \in \{x_{1,r_1}, x_{1,r_2}, ..., x_{1,r_{s_1}}, x_{2,r_1}, ...\}$ such that $x_{i,s} = t_{i,s+1} - t_{i,s}$ where $t^*_i \leq t_{i,s+1}, t_{i,s} \leq t^*_{i+1}$.

Moreover, the expression $2\lambda_i(\sum_j x_j)$ has a chi-square distribution with 2n degrees of freedom. Based on that fact it is possible to generate a sequence of events $T(n_D)$ in expression (3) by using Monte Carlo simulation.

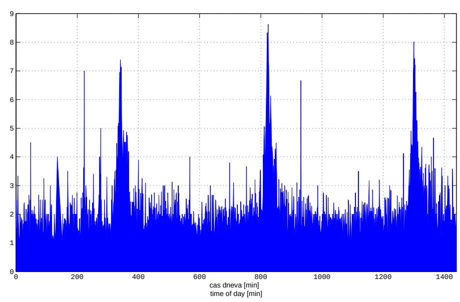

Fig. 3 The average number of events per minute during the day. Peaks at 6am, 2pm an 10pm are visible because of the shift changes.

ISBN 978-3-901608-32-2

4 A case study

The approach above has been applied to a case study in manufacturing industry. The underlying plant employs 60 workers per shift. Fig. 3 presents the frequency of events on daily basis.

The learning set includes 10 working days. Based on the profile of the $\lambda-$parameter has been estimated. Based on the estimated profile a Monte Carlo simulation is applied to generate event sequences for 83 days. Figure 4 shows that the predicted density of events fits extremely well the actual one.

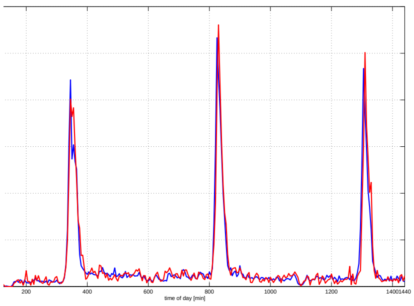

Fig. 4 Cross-validation of the estimated $\lambda-$profile: red and blue graph represent the predicted and actual density of events on a 83 days horizon (the estimates are obtained on a 10-days record).

In our optimization procedure we used actual cost parameters of c_w = 4.6 and c_0 = 1500.

During the optimum search, a new histogram is calculated for each time a new number of terminals is selected. Fig. 5 shows histograms for N = 1, 2, 3. Critical expected time approaches 0 with increasing number of terminals.

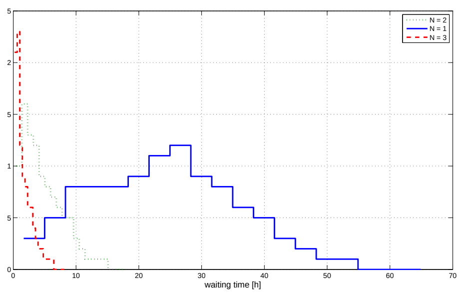

Fig. 5 Histograms of accumulated waiting time for various numbers of terminals N = 1, 2, 3. When increasing the number of terminals, critical expected time approaches 0.

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

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

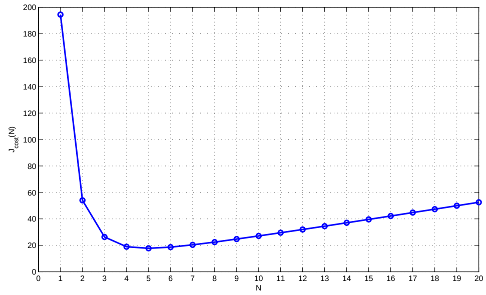

Fig. 6 Criterion function J_{cost}, for a given critical value $\alpha = 0.05$, shown as a function of the number of terminals N. The lowest value of 17,73 is reached at N = 5.

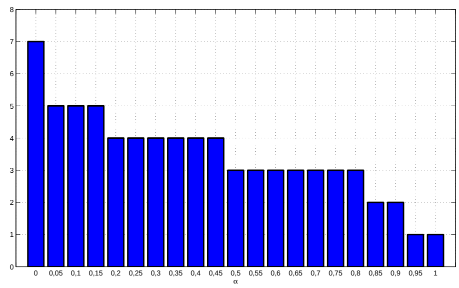

Fig. 7 The optimal number of terminals in dependency of parameter $\alpha \in [0,1]$.

5 Discussion

The results above need some comments:

1. The solution depends very much on the quality of learning data set. Special attention has to be paid to that issue. 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 waiting times in dependance of the number of terminals. Moreover, Fig. 6 is helpful in figuring out the cost of additional redundancy. More precisely, though the optimum is N*=5, the costs to install one more or even 2 additional terminals are almost negligible. However, the overall system s much more robust to potential failures and downtimes of a terminal.

4. In this stage we did not take into consideration the topographical distribution of terminals. Instead, we were only searching for the optimal number of them assuming that terminals are distributed uniformly along the production plant and the paths between work places and terminals do not differ much.

6 Conclusion

In this paper we addressed the problem of optimal terminal arrangement in the production plant, which has been formulated in terms of optimization of a stochastic criterion function. Main goal of this study was to develop the algorithm, which will enable to determine the optimal number of terminals in manufacturing industries. The proposed probabilistic criterion function takes into account two types of costs: those due to waiting times and those caused by the installation of the terminals. The main contribution refer to the estimation of time varying density of events on short training data sets.One possible upgrade of the presented solution would also consider the topographical part of the problem. Namely, it is not possible to set up a terminal at any site in the production plant. Availability of power and communication outlets should also be considered. Terminals can also communicate wireless, but acquisition costs in that case rise. That is another possible upgrade to presented solution.

7 Acknowledgement

The authors gratefully acknowledge the Slovenian Research Agency for support through the Research Programme P2-0001.

8 References

[1] S. Boyer. *SCADA: Supervisory Control and Data Acquisition*. ISA, Research Triangle Park, 1999.

[2] T. Wallace and M. Kremzar. *ERP: Making It Happen*. John Wiley & Sons, New York, 2001.

[3] http://www.noax.com.

[4] L. Wasserman. *All of Statistics: A Concise Course in Statistical Inference*. Springer, New York, 2004.

[5] A. Elfessi and D. M. Reineke. A Bayesian look at classical estimation: the exponential distribution. *Journal of Statistics Education*, 9:online, 2001.

