Drug Warehouse Optimization: an Approach Based on Response Surface Method

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Abstract: This paper aims at quantitatively assessing the effects of different drug warehouse configurations, on the resulting hospital average stock and service level. A case study has been analysed, taking into account three echelons: suppliers, central stock, and hospitals/pharmacies. A model of several supply chain configurations has been modelled with the use of the simulation software Arena, and a vast part of it has been programmed in VBA, implementing a graphical user interface, giving more flexibility to the simulations. Specifically, 64 supply chain configurations have been examined, stemming from the combination of many supply chain design parameters, namely: number of pickers; stock policy; required number of bay areas, and the presence or less of the pick to box system. For each designed configuration, hospital stock and service level analysis are computed. A DoE (Design of Experiments) analysis has been executed on each simulation to know which input variables are statistically significant. Finally, using Response Surface Method, the DoE results have been used to optimise the combination of the considered factors.

Keywords: Drug Management; Warehouse optimisation; Response Surface Method; Design of Experiment; Simulation model

1.Introduction

In the last years, during which globalisation and competition considerably increased, more and more companies are dealt with the problem of how to control the flow of goods from the production locations to the points of demand (Żak and Moeller, 2011). Indeed, wrong policies for warehouse management produce high levels of inventory and excessive costs. Hitherto, to resolve this problem, different branches of operations research developed their models and solution approaches. Determining the best facility design is a classical industrial engineering problem (Ekren and Ornek, 2008). Thus, industrial engineers were often known as efficiency experts and were interested in determining layouts to optimise some measure of the plant efficiency. As mentioned by Flynn et al. (1995), a plant layout study might include the minimising the investment required in new equipment, the minimising the time required for production, the utilising the existing space most efficiently, minimising the materials handling cost, facilitating the manufacturing process.

By a literature review, regarding facility layout, it is possible to highlight that a host of heuristic algorithms have been explained, and, many software packages exist to solve the layout problem (Ekren and Ornek, 2008). Many plant layout design procedures are finalised to minimise a static measure of material handling time or cost, but, at the same time, the performance of a manufacturing system can also depend on many factors such as the batch sizes of parts, scheduling rules, downtimes, and setup times on machines. So, there is an exigency to define the combination and level of these factors for optimising the measure of performance.

In particular, regarding the International healthcare systems, they are under increasing pressure for reducing waste and eliminating unnecessary costs, and contemporarily still improving the quality of patient care (Piccinini et al., 2013). Consequently, healthcare logistics and supply chain management are moving under a great deal of scrutiny from both practitioners and academics (Battini et al., 2009a). Pharmaceuticals represent a significant portion of the costs in the healthcare industry due to the significant costs of these products and their storage and control requirements. Progressive changes in the markets, increasing globalisation and the consequent new business prospects are currently imposing the need for a continuous reconsideration of business management methods (Bertolini et al. 2011). In this light, according to Mohanty and Deshmukh (2000), Business Process Reengineering (BPR) has become a key factor, capable of facilitating the creation of an evolutionary structure that ensures effective organisational changes. The fundamental philosophy of the business process re-engineering is an approach to change management, resulting in best practices (Bevilacqua et al., 2005).

Specifically, this paper aims at analysing the effects of the pre-defined process parameters on a manufacturing system by conducting a simulation-based full factorial design. Many existing plant layout design procedures attempt to minimise a static measure of material handling time or cost, but the performance of a manufacturing system can also depend on other factors such as the batch sizes of parts, scheduling rules, downtimes and setup times, and demand. Thus, there is the need to determine the combination and level of these factors so that a measure of performance is optimised.

The performance measure is defined concerning the average flow time of parts through the storage system. The experimental design is performed by simulating the system using the ARENA© 14.0 simulation software (Kelton et al., 2004) and analysing outputs using the modeFRONTIER© software. In the proposed study, the data and the information used for simulation study have been collected among the Ancona hospitals (Italy).

The rest of the paper is organised as follows: first, in Section 2 the necessary background and motivation for the paper have been provided. Then, in Section 3 the definition of the problem has been described, referring to the Unit Care of the "Vast Area" Marche, Italy, giving the details of the simulation model and explaining the design factors considered. Analysis of responses of simulation runs and the designed experiments, including the main effects and interactions between the factors, are detailed in Section 4. Finally, we present our conclusions and directions for future research.

2. Background and motivation

2.1 Literature review

The warehouse optimisation problem, especially in this time of crisis, is crucial for a company that wants to reduce costs and increase profits. For this reason, literature presents many studies about it.

In their work, Żak and Moeller (2011) analyse the increasing warehouse order picking performance by sequence optimisation. Specifically, it is possible to note that, in the case of a line of storage organised with the policy (LSO Optimization Sequence Line), the optimal path can be calculated with the minimum time to a specific lot. From the various tests, carried out in the project, they had a potential improvement of 7.4%.

Most interesting is the study of Razmi et al. (2013) regarding the pharmaceutical distribution in Tehran. In fact, they proposed a development bi-objective to redesign and optimise a warehouse. In this model, the starting point is to eliminate the stock, and if it is not possible, to try to place them in other stores. They used the augmented ε- constraint approach for minimising the warehouse costs and increasing the fulfilled orders. This approach has been simplified, removing some critical variables such as the uncertainty on the efficiency of the obtained solutions.

Önüt et al. (2008) analysed a multiple-level warehouse layout design problem. The purpose of the study was to provide a configuration of the shelves in the warehouse to multilevel to minimise the costs of storage annual. In particular, much importance has been attributed to the position of objects in various shelves to ensure the best turnover depending on the demand for the product. It is given a specific weight to each product according to their request and thus a suitable location on the shelves.

In the warehouse optimisation problem, it is essential to fulfilling the demand. To avoid this problem, Rath and Gutjahr (2014) deal the warehouse location-routing problem in disaster relief. A multi-objective has been resolved using the δ-constraint approach: the minimising of total costs, the minimising of the operative costs, and the maximising of the fulfilled demand. It is important to highlight that accomplish several goals can make them come into conflict with each other (Poulos et al. 2001). Poulos et al. (2001) ensure an increase in the diversity of optimal solutions using fuzzy rules that ensure optimal use of resources, better service to the customer, and the costs reduction.

Most relevant is the paper of Chang et al. (2007) regarding the picking phase optimisation. In fact, they proposed a new model for the warehouse order picking optimisation problem (W-OPP) to resolve NP-hard problems and, in so doing, improve the used genetic algorithm.

Moreover, in his paper, Ganeshan (1999) presents a near-optimal (s, Q)-type inventory policy for a production/distribution network with multiple suppliers replenishing a central warehouse, which in turn distributes to a large number of retailers. The proposed model is a synthesis of three components such as the inventory analysis at the retailers, the demand process at the warehouse, and the inventory analysis at the warehouse. In so doing, the key contribution of this model is the seamless integration of the three components to analyse simple supply chains. Most important for the proposed paper was the research of Battini et al. (2009b), in which, they have analysed the problems about material centralisation/decentralisation, storage policies and assembly feeding problem in different and independent ways, while the problem needs an integrated approach. A multi-factorial analysis has been performed during this experiment and will validate the introduced framework to reach the maximisation of efficiency and flexibility.

Always using a simulation-based experimental approach, Bouslah et al. (2013) illustrated the efficiency of the control policy. Thus, numerical experiments and thorough sensitivity analyses are provided for illustrating the robustness of the resolution approach and the effectiveness of the proposed control policy. Moreover, they observed and discussed some interesting behaviours regarding the impact of different parameters on the optimal decision variables. Regarding the pharmaceutical activities, Chow and Heaver (1994) identified how logistics costs are composed: 27% for the cost of supplies, 4% for time spent by clinical staff on logistics tasks, and 15% for employees assigned to logistics duties, including material management, nutrition and laundry staff. For these reasons, it is imperative to resolve the warehouse optimisation problem, in a pharmaceutical system.

2.2 Response Surface Method

Experimental design and optimisation are tools that are used to systematically examine different types of problems in the research, development and production fields. It is important to highlight that if experiments are performed randomly, the result obtained will also be random. For this reason, it is a necessity to plan the experiments in such a way that the interesting information will be obtained (Lundstedt et al. 1998).

It is reasonable to assume that the outcome of an experiment, y, is dependent on the experimental conditions, and this means that the result can be described as a function based on the experimental input variables, x1, x2, xk. More specifically, when a list of variables to be investigated has been completed, it is possible to choose an experimental design to estimate the influence of the different variables on the result (Woods et al., 2008). In particular, linear or second order (see equations (2), (3) and (4)) interaction models are conventional, such as in full factorial or fractional factorial designs. Moreover, the former design is limited to determining the direct influence of the variables, while the latter allows for interaction terms between variables to be evaluated as well. Finally, the variables with the most relevant influence on the procedure can be identified (Khuri and Mukhopadhyay, 2010).

In a factorial design, the influences of all experimental variables, factors, and interaction effects on the response are investigated. If the combinations of k factors are investigated at two levels, a factorial design will consist of 2k experiments. In particular, the levels of the factors are given by – (minus) for low level and + (plus) for high level. A zero-level is also included, a centre, in which all variables are set at their mean value.

Used simultaneously with the Design of Experiment (DOE), Response Surface Methodology (RSM) is a group of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimise a response, or output variable, which is influenced by several independent variables, also said input variables. As said before, an experiment is a series of tests, called "runs", in which changes are made in the input variables, *x1, x2...xk*, to identify the reasons for changes in the output response, *y*. Originally, RSM was developed to experimental model responses (Box and Draper, 1987), and then migrated into the modelling of numerical experiments. More in general, such a relationship is unknown but can be approximated by a low-degree polynomial model of the form:

$$y = \boldsymbol{f(x)\beta} + \varepsilon \tag{1}$$

where *x = (x1, x2, . . . , xk)'*, *f(x)* is a vector function of *p* elements that consists of powers and cross- products of powers of *x1, x2, xk* up to a certain degree denoted by *d* (≥ 1), β is a vector of *p* unknown constant coefficients referred to as parameters, and is a random experimental error assumed to have a zero mean.

Specifically, two models are commonly used in RSM. It is possible to highlight that, these are specific cases of the equation (1) and include the first-degree model (d = 1), or linear model without interactions,

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon \tag{2}$$

alternatively, the first-degree model with interactions,

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{3}$$

moreover, the second-degree model (d = 2), or quadratic model,

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum\sum_{i<j} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \varepsilon \tag{4}$$

The purpose of considering a model such as (1) is threefold. First of all, it allows establishing a relationship, albeit approximate, between the input and output variables, which can be used to predict response values for given settings of the control variables. In the second place, using it, it is possible to determine, through hypothesis testing, the significance of the factors and, finally, the determination of the optimum settings for the input variable is possible, resulting by the maximum (or minimum) response over a specific region of interest. A series of n experiments should first be carried out to achieve the above three objectives, in each of which the response y is measured (or observed) for specified settings of the control variables. Thus, the totality of the designed settings constitutes the so-called response surface design, which can be represented by a matrix, denoted by D, of order $n \times k$ called the design matrix. In particular, the choice of design depends on the properties it is required, or desired, to have. Some of the design properties considered in the early development of RSM include the Orthogonality and Rotability.

As said before, one of the primary objectives of RSM is the determination of the optimum settings of the control variables resulting in a maximum (or a minimum) response over a specific region of interest. To obtain this condition, having a "good" fitting model that provides an adequate representation of the mean response is required (Fedorov, 1972). In fact, optimisation techniques used in RSM depend on the nature of the fitted model. In particular, for first-degree models, the method of steepest ascent (or descent) is a viable technique for sequentially moving toward the optimum response. Myers and Montgomery (1995) explained in detail the method.

3. The problem description

The methods for analysing and consequently redesigning a process, typical of business re-engineering, can also be applied to drug management processes to identify any shortcomings and improving their efficiency. These methods are applied to a specific stage in the drugs management and distribution in a particular Italian area, denominated "Vast Area", and approximately equal to the Ancona Province territory. We focused on the inventory management at a local storage unit.

At the logistic distribution stage, the current situation can be shown by the diagram in Figure 1. Each hospital has its pharmacy and hospital warehouse, and each supplier can supply all the hospitals. Moreover, 154 pharmacies in the considered region have been examined.

The simulation software Arena, which is particularly proper for this kind of problems, has been used in this study. Due to a large number of variables to take into account, and a logic model quite complex, a significant part of the model has been programmed with the use of VBA (Visual Basic for Application).

The different simulated scenarios, using DoE analysis, allowed us to optimise a hypothetic central warehouse for the whole "Vast Area", analysing the considered factors. To define the central warehouse organisation, the actual demand of each actor of the "Vast Area" has been analysed, considering the structural features imposed. Analysing the actual situation, it has been possible to define the supplying frequency and the average of the daily demand. Moreover, the European standard has been

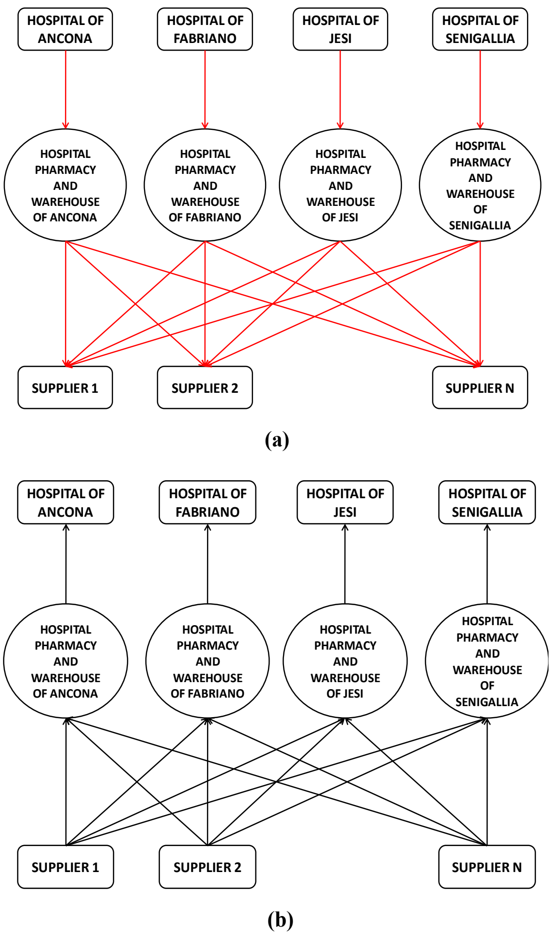

Figure 1: Actual distribution model in the "Vast Area". In particular, in (a) information flow has been represented, in (b) the material flow

used for defining the amount of pallet and boxes for each delivery in the warehouse.

All of these considerations have been modelled used probabilistic distribution, summarised in Table 1. Moreover, the initial configuration is composed of two incoming bays, two outgoing bays. The handling in the central warehouse will be guaranteed by three forks lift and three stacker cranes. Also, the pallet inventory can store 1500 pallets, and the boxes inventory has a capability of 8000 boxes. The whole warehouse structure will be placed in an area of 3500m2. Figure 2 shows the realised base model of the central warehouse.

The response of each simulation has been identified in the stock level of pallet, boxes and rolls in the warehouse area. Each stock level has been considered about the cost of each scenario to have a single output. This response variable has been taken considering that the material in the warehouse is constituted by drugs that cannot be preserved in non controlled condition for a long time.

This paper aims at not only to investigate the performance measure of a warehouse system that is the connection between pre-defined factors on average flow time of the parts through a system but, at the same time, how it is improved by the appropriate levels of these factors set by using simulation-based experimental design. Specifically, the flow time is the time that a part spends in the system from raw materials stage to the finished-goods area. In the proposed case, it will be considered

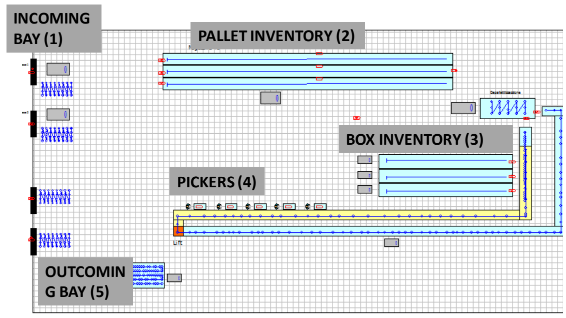

Figure 2: The hypothetic central warehouse for the whole "Vast Area", base model (1).

as the time that a part spends in the system from the storage stage to the shipping area.

Table 1: simulation parameters.

Features Name	Probabilistic Distribution	Unit dimension
Supplying Frequency	Norm(72,16)	Hours
Hospital/Pharmacies Orders Frequency	Norm(24,8)	Hours
Number of supplier's deliveries	Uniform(4,6)	Daily deliveries
Number of delivered pallet	Uniform(12,33)	Pallets
Number of box per pallet	Uniform(16,45)	Boxes
Number of drugs per box	Norm(100,40)	Drugs
Number of daily hospital orders	4	Orders
Number of daily pharmacies order	Norm(30,5)	Orders

The selected factors of interest which are thought to have essential effects on the performance measure include the storage policy, the number of the pickers, the number of bays area, and the presence of the pick to box system, as shown in Table 2. The model has been simulated using these factors at different levels. The responses from the simulation runs are subsequently analysed using the design of experiments approach to determine the primary and interaction effects of the considered parameters.

4. Results and Discussion

Before the simulation phase, the DoE analysis has been done to verify that the considered input factors were relevant. To calculate the Response Surface, 64 scenarios have been simulated, considering the variability range of each factor. Table 3 shows the results of the sub-set simulation according to the experiment set, used for the DoE analysis. In this first step, it is sufficient to consider only the minimum and maximum value of each range. The response to each scenario has been obtained as the average of 100 simulations. Table 4 shows the effects of each factor considered in the analysis.

Table 2: Independent variables for DoE analysis.

Factors	Variables Name	Range	Description
A	Stock policy	[0 1]	The 0 value identify the "Random" stock policy and 1 "ABC" stock policy.
B	Number of pickers	[3 10]	
C	Number of the outgoing bay	[2 8]	
D	Presence of the pick to the box system	[0 1]	The 0 value identify the absence of pick to box system, and one its presence.

Table 3: results of the experiments for DoE analysis

N.	Name	A	B	C	D	Response	σ
1	(1)	-1	-1	-1	-1	2469,15	1,15
2	A	1	-1	-1	-1	2372,70	1,30
3	B	-1	1	-1	-1	3680,79	1,89
4	AB	1	1	-1	-1	3502,88	0,84
5	C	-1	-1	1	-1	2000,06	0,77
6	AC	1	-1	1	-1	1961,46	0,97
7	BC	-1	1	1	-1	3114,34	3,15
8	ABC	1	1	1	-1	3001,82	2,54
9	D	-1	-1	-1	1	1815,13	0,66
10	AD	1	-1	-1	1	1791,99	1,51
11	BD	-1	1	-1	1	2866,94	1,53
12	ABD	1	1	-1	1	2779,88	1,90
13	CD	-1	-1	1	1	1547,63	0,40
14	ACD	1	-1	1	1	1549,59	0,63
15	BCD	-1	1	1	1	2511,01	2,15
16	ABCD	1	1	1	1	2454,01	0,61

Table 4: the value of the effect of each DoE factor

SINGLE EFFECT		2° ORDER EFFECT		3° ORDER EFFECT		4° ORDER EFFECT	
A	-73,85*	AB	-34,85*	ABC	1,60**	ABCD***	-0,23
B	1050,37*	AC	22,32**	ABD	4,13**		
C	-392,43**	BC	-44,95*	ACD	-8,42*		
D	-598,47*	AD	32,52**	BCD	1,76*		
		BD	-73,56**				
		CD	94,55*				

In particular, it is possible to highlight that the factors A (stock policy), B (number of pickers), and D (the presence of pick to box system) influence the system response with direct proportionality. Conversely, the factor C (number of the outgoing bay) has an indirect influence on the system response. Moreover, it is possible to see that the factor B (number of pickers) is the most relevant. Changing its value, the system response has the highest value. Moreover, all of the relevant scenarios depend always on the factor B change. This consideration is possible also analysing the effect value in Table 4; in fact, the effect of factor B has the highest value (~1050). Once verified the significance of the considered independent variables for the optimisation, all of the 64 possible combinations have been simulated 100 times, to define a sufficient number of point for calculating the RS. Mainly, considering that the effect of ABCD scenarios as not relevant for the system, to define the Response Surface, the third order model has been used. It is also important to highlight that a constraint on the surface response has been added. In fact, according to the fact that the response of the system is the cost of the stock level, it cannot be minor than 0.

The coefficient for the Response Surface Method has been calculated using ModeFrontier software. Figure 3 highlights the DoE considerations regarding the proportionality of "pickers" and "policy" factors on the response, in fact, it is possible to see as the realised response surface confirms these considerations. It is impossible to plot the whole response surface having used four factors.

Table 5: the optimal combination

NUM.	*A*	*B*	*C*	*C*	*Y*	*NUM.*
72	1	3	8	1	1559,15	1559,15

Obtained the Response Surface, always using ModeFrontier, it has been possible to minimise the response system, calculating the optimal combination of the considered factors. To avoid this problem, it has been used the Taguchi's experiment design, as suggested by Tsai (2002). In fact, Taguchi Methods support the methodologies for analysis and guide a selection of the optimum level. Analysing all of the Surface Response results, the optimal combination is shown in Table 5. In other words, the optimal factors combination is identified by the application of the "ABC" stock policy, three pickers and eight outgoing bays, and the presence of the pick to box system.

Conclusion

Based on a discrete-event simulation model, reproducing a pharmaceutical warehouse of a healthcare system, a quantitative assessment of the effects of different configurations on the inventory levels has been provided, in the observed system. This analysis covers 64 possible configurations, resulting from the combination of several design parameters. For each scenario, the system performances have been computed, starting from simulation outcomes and several input parameters available in the literature. A statistical effect analysis has been performed, to identify the possible significant impact of single/combined design parameters, on the resulting inventory and demand variance amplification. The control of a warehouse system is usually complex with a vast number of interrelationships between actors. The approach that can accommodate such complexity is that of breaking the control problem into a hierarchy, which emphasises the interrelationship of the manufacturing processes. The simulation model was run iteratively under different decision

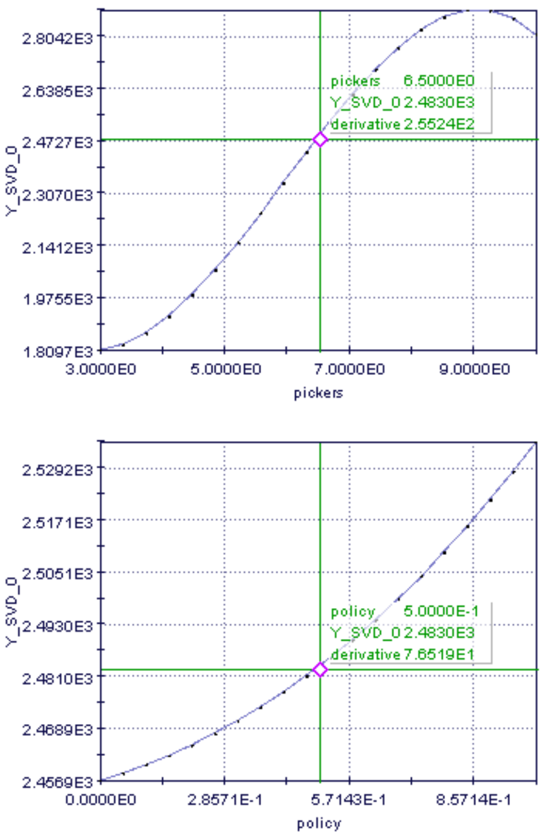

Figure 3: Response surface depending on "pickers" and "policy" factors.

options to identify the system to find the optimum results. Because the system comprises four operational parameters, all possible interactions require 224 simulation runs. Hence, the use of Taguchi Methods in the simulation has been studied, and the results show that these methods can be useful in reducing the number of experimental trials (only 64 simulation runs have been used) needed to determine the best operating parameters.

In this paper, a review of different designs for fitting response surfaces has been given, and a desirable design of experiments should provide a distribution of points throughout the region of interest that means to provide as much information as possible on the problem. Moreover, the proposed approach highlights that RSM and DoE can be used for the approximation of both experimental and numerical responses.

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