Resizing the Workforce for Picking Activity: Application in the Fashion Sector

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Abstract: Order picking is one of the most critical activities in warehouses as being the most labor intensive with costs that can be up to 55% of total warehouse expenses. In this context the right sizing of picking workforce is decisive and has to guarantee a satisfactory service level. In this paper, workforce resizing for warehouse picking activities, was investigated in the light of the growth of receptivity required by one of the commissioning firms. Given the high labour intensity in the picking activities, the first phase of our analytical framework for the workforce resizing includes a statistical validation of the law of diminishing returns, which can be viewed as an effect of the free-rider behaviour, and then (i.e., second phase) a fitting approach of the said law; the curve that best fits the historical data is used in the third phase to forecast the future productivity. The last phase is made of an analytical procedure to derive the average future required number of ordinary and overtime pickers. We applied our framework in a real warehouse for a firm in the fashion sector, results highlighted a necessity for workforce increase, compared to the "as-is" scenario; this will allow the firm to strategically identify future workforce size requirements, from a cost-based perspective.

Keywords: warehouse, redesign, workforce, picking, analytical framework

1.Introduction

The warehouse is a fundamental facility to store and consolidate products, reduce transportation costs, achieve economies of scale in manufacturing or purchasing (Bartholdi and Hankman, 2016), while providing shorter operational or logistical response time (Gong and De Koster, 2008). Warehouses can be classified based on different criteria. Ghiani, Laporte and Musmanno (2004) classified them into production or distribution centres and proposed a further classification based on their ownership: company-owned, public, and leased warehouses. Another possible classification is proposed by Bartholdi and Hankman (2016) according with the customer service type: retail distribution centre, with service parts distribution centre, a catalogue fulfilment or e-commerce distribution centre. Even if warehouses are heterogeneous, the material workflow typically includes the following warehouse operations: receiving, put away, internal replenishment, order picking, accumulating and sorting, packing, cross docking, and shipping (Tompkins, J.A, White, J.A., Bozer, Y.A., Tanchoco, 2003). Between these activities, the "order picking", that is the retrieval activity of products to fulfil orders, is crucial to ensure the right service level for customers. It is also an expensive activity that, according to Bartholdi and Hankman (2016), contributes to about 55% of the operational costs. Indeed, order picking has been well-researched in literature where we can find significant research reviews (e.g., de Koster, Le-Duc and Roodbergen, 2007; van Gils *et al.*, 2018). The main problems arising in the design of an order picking system may be addressed through three main levels: strategical, tactical and operational levels (Anthony, 1965; Rouwenhorst *et al.*, 2000). At the strategical level, the selection of automation intensity as well as the equipment for the material handling represents the main problems. The reader can refer to Rouwenhorst *et al.* (2000) and Davarzani and Norrman (2015). Actually, the decisions taken at this level influence and constrain the subsequent levels. At the tactical level, the main problem arising concerns the resource sizing in terms of storage capacity, relative warehouse area as well as the workforce (van Gils *et al.*, 2018). Finally, for the operational level, the main problems identified as job assignment and batch creation (Gu, Goetschalckx and McGinnis, 2010). In literature we can find various review that focused on an individual planning problem: Rouwenhorst *et al.* (2000), Davarzani and Norrman (2015), (Marchet, Melacini and Perotti, 2015), (Gong and de Koster, 2011). Howehever we have a scarsity of paper that combine different different planning problem has demonstrated in a dedicated review (van Gils *et al.*, 2018) where ten different planning problem were identified but only 26 over a total of 45 possible combination of these planning problem have been addressed in literature. In this context we position this research paper at the tactical level, with the aim of re-sizing the workforce and re-designing the picking area of an outsourcing warehouse of fashion items in order to meet the growth of receptivity forecasted for year 2025 and this is a first attempt to fulfil the individuated gap. Since the various firms are managed in dedicated areas that are clearly separated, we refer to the warehouse as the area dedicated to the commissioning firm taken into consideration. As already stated, the decisions taken at the strategical level influence and constrain the subsequent levels, and this is confirmed in our case. Indeed, at the strategic level, the intensity of automation has been set to the lowest level possible with a full manual order picking system. This aims to limit fixed investments since the contracts with the commissioning firms are renewed on average every five years. Another constraint refers to the warehouse layout, which must be redesigned by making as few changes as possible to reduce costs. As established in previous literature (Pohl, Meller and Gue, 2009), the manual picking activities highly impact the warehouse performances, therefore flying-V and fishbone layouts are proper options to be able to reduce the travel distance up to 20% in single command operations. Nonetheless, two rules are often adopted in practice to design warehouses: i) picking aisles have to be straight and parallel; ii) cross aisles, if present, have to be straight and meet the picking ones at right angle (Gue and Meller, 2009). The concerned warehouse implements these two rules, and this is presented in detail in the case study, but it can be anticipated that the aisles were designed to maintain their characteristics unchanged except their isles length to meet the growth of the required receptivity. For the purpose of workforce re-sizing, and in order to derive the expected number of operators required in 2025 we investigate an analytical framework that can be useful for practitioners in similar situations. First, the researchers analysed data about the workforce productivity in 2019 and validate statistically via ANOVA test (Shaw and Mitchell-Olds, 1993) the hypothesis that the mean individual productivity depends on the number of operators involved in picking activities. Specifically, we prove that the mean individual productivity decreases with respect to increased number of operators. This confirms the law of diminishing returns (Shephard and Färe, 1974) and the so-called "freeride behaviour" (Albanese and Van Fleet, 1985) that affect groups, i.e. "In a wide range of situations, individuals will fail to participate in collectively profitable activities in the absence of coercion or individual appropriable inducements" (Stigler, 1974), and this is related to the group size. After having proved statistically that a freeride behaviour affects the groups of worker a firm can implement various strategy, the most used in literature is the creation of competition among groups (Erev, Bornstein and Galili, 1993), (Chen, 2020). After conducting the statistical validation, researchers fit the law of diminishing returns by means of a power law with plateau relationship as being the best-fitting curve among those tested. Then, they use this curve to forecast the productivity distribution by varying the number of operators. This is the input of the last step of this research, which aims to derive the expected number of both ordinary and overtime operators necessary to guarantying the set customer service level. As far as our knowledge goes this is the first wok that address the problem of workforce resizing including a fitting procedure to forecast the workforce productivity in relation to the law of diminishing return and to the free ride behaviour while taking into consideration also the re-design of the picking area. This enables our work to be exploited by practitioners in situations that requires a workforce resizing for picking operations in a context of mainly manual work. This paper is structured as follows: Section 2 contains the notation and the framework of the proposed research framework, which will be explained step by step; Section 3 reports for the case study; and Section 4 provide conclusions and suggestions for the future research progress.

2. Notation and framework

This section contains the adopted notation and the research framework.

$t = 1..T$: days in the reference period.
h_t: total number of items picked in day-t, $\left[\frac{unit}{day}\right]$.
O_r: maximum number of operators at work observed in the reference period.
O_{min}: minimum number of operators at work in the historical reference period.
O_{max}: maximum number of operators allowed for the future.
$i \in I = \{O_{min}, O_{max}\}$: number of operators [op].
i_t: number of operators at work in day-t.
T_i: number set of days where i-operators worked with $i: O_{min} < i \leq O_r$.
$\bar{h}_t$: mean individual hourly productivity in day-t, $\left[\frac{unit}{h*op}\right]$.
H_i: set of mean individual hourly productivity when i-operators worked.
P_i: mean hourly individual productivity in a group of i-operators in the reference period, with $i: O_{min} < i \leq O_r$, $\left[\frac{unit}{h*op}\right]$.
V_i: variance of the mean hourly individual productivity in a group of i-operators in the reference period with $i: O_{min} < i \leq O_r$, $\left[\frac{unit}{h*op}\right]^2$.
P'_i: forecast of the mean hourly individual productivity in a group of i-operators with $i: O_r < i \leq O_{max}$, $\left[\frac{unit}{h*op}\right]$.
V'_i: forecast of the variance of the mean hourly individual productivity in a group of i-operators with $i: O_r < i \leq O_{max}$, $\left[\frac{unit}{h*op}\right]^2$.
P_s: set of the mean hourly individual productivity defined as the union of P_i and P'_i.
V_s: set of the variance of the mean hourly individual productivity defined as the union of V_i and V'_i.
C_k: Class created to subdivide the h_t with $t = 1..T$, $k = 1..K, K <= T$
$[l_k, u_k[$:lower and upper bound for $C_k$with $l_{k+1} = u_k$ with $k = 1 \dots K$, $\left[\frac{unit}{day}\right]$ where only the last class contains its upper bounds.
w = width of the classes calculated as $\frac{u_K - l_1}{K}$.
m_k: centre of C_k , with $k = 1 \dots K$, $\left[\frac{unit}{day}\right]$.
f_k: frequency of C_k with $k = 1 \dots K$.

g_p: % forecasted growth for the picked quantities.
E_p: expected number of ordinary operators required.
E_s: expected number of overtime operators required.
m'_k:center of class-k increased by g_p with $k = 1 \dots K$.
SL: service level in terms of percentage of h_t to be delivered in t.

2.1 Framework

This section illustrates the research framework implemented:

i) Data collection: researchers collected all the relevant data for the further analysis. Basically, there is a need to derive the mean historical individual productivity of pickers based on their number and subdivide in ranges the outbound quantities in the historical reference period. Collected data includes the total picked quantities and the number of pickers at work dedicated to the activity full time (i.e., 8 hours in this case) for the reference period. Additionally, researchers need all the information about the current warehouse layout, capacity, material handling system and constraints for its expansion as well as growth percentage forecasted for both the maximum storage capacity and the picked quantities.

Input data:

- Days in the reference period indexed as: $t = 1..T$.
- Total number of items picked per day (h_t).
- Number of operators at work per day (i_t).
- Maximum number of operators allowed in the future (O_{max}).
- Classes in which we subdivide the productivity in order to obtain a significant incidence of every class. This study considers significant a class incidence higher than 1% ($[l_k, u_k[$, $k = 1 \dots K$). The said classes are used to refer the further calculations to their mean values, that is their probability masses (i.e., relative frequencies f_k).
- Service Level (SL).

Hp1: 8 working hours per day per operator are allowed.

Hp2: the mean individual productivity of every group of operators is normally distributed with mean and variance respectively equal either to P_i and V_i, with $i: O_{min} < i \leq O_r$, or to P'_i and V'_i, with $i: O_r < i \leq O_{max}$.

Derived input data:

- $T_i = \{t: i_t = i\}$
- $\overline{h_t} = \frac{h_t}{8 * i_t}$
- $H_i = \{\overline{h_t}: t \in T_i\}$
- $O_r = max_{t=1..T}\{i_t\}$
- $P_i = \frac{\sum_{t \in T_i} \overline{h_t}}{|H_i|}$, with $i: O_{min} < i \leq O_r$
- $V_i = \frac{\sum_{t \in T_i} (\overline{h_t} - P_i)^{\wedge}2}{|H_i|}$, with $i: O_{min} < i \leq O_r$
- $m_k = \frac{(u_k - l_k)}{2}$
- $f_k = Pr\{l_k < h_t \leq u_k\}$
- $m' = m_k * (1 + g_p)$
- $P_s = \{Pi \cup P'i\}$
- $V_s = \{Vi \cup V'i\}$

ii) ANOVA: we carry out an ANOVA test on the elements of H_i (i.e., response) to statistically validate that they belong to different populations varying with the number of employed operators (i.e., factor). In particular, we use an un-balanced ANOVA (Shaw and Mitchell-Olds, 1993; Schiff and D'Agostino, 1996) because the samples showing different cardinalities.

iii) Fitting of the law of diminishing returns: we fit the curves that describe decreasing trends for both of P_i and of V_i by increasing the number of operators. The said curves are then used to forecast P'_i and V'_i, respectively, when $(O_r < i \leq O_{max})$. In particular, we use a linear model (1), a quadratic model (2), a power law of the first (3) and second order (4) as well as a negative exponential model (5). We benchmark them in terms of Squared Sum of Errors (SSE). The research reports on the below the examples not only of the curves for P'_i but what they hold also for V'_i.

$$P'_i = a * i + b \quad (1)$$
$$P'_i = a * i^2 + b + c \quad (2)$$
$$P'_i = a * i^b \quad (3)$$
$$P'_i = a * i^b + c \quad (4)$$
$$P'_i = a * e^{i*b} + c \quad (5)$$

At the end of this step, researchers choose the best-fitting models, i.e. those giving the lowest SSE, and calculate the forecasted P'_i as well as V'_i till O_{max}.

```
Procedure n_op
[find,n,qleft]=n_op(q,LS,Ps,Vs)
find=false; n=0; qleft=0;
for (every number of operator i in
Omin..Omax)do{
if (i is comprehended in [Omin,Or]) then
x is Normal distributed
with mean= Pi*i*8 and variance= Vi*i^2*8^2
else
x is Normal distributed
with mean= P'i*i*8 and variance= V'i*i^2*8^2
end-if
c=Cumulative density function of x
calculated in q
          if (c>LS) then
                    find=true;
                    n=i;
       end-if
 end-do
 if (find=false) then
n=Omax;
find=false;
qLeft=q*(1- c);
end-if
end
```

```
Procedure Exp_op
[Ep,Es]=Exp_op(K,fk:k=1…K,Ps,Vs,m'k:k=1…K)
Lek:number of ordinary operator required for
class-k of picked quantities;
LSk: number of straordinary operator required
       for (every k-class)do{
              [find,n,qleft]=n_op(q,LS,Ps,Vs);
              Lek=n;
              if (find=false)
                     [find,n,qleft]=n_op(qlef,
              LS);
```

```
        if(find=true)
                Lsk=n;
        else
display('We cannot satisfy the demand of the %k% class the maximum number of operators have to be increased')
end-do
     Ep=Cross Product(Lek,fk);
     Es=Cross Produc(Lsk,fk);
-------------------------------------------------------
```

iv) Analytical procedure: we derive the expected number of required operators by means of the procedure explained in the form of the following pseudo-code.

The first procedure is used to find the required number of operators to pick a certain quantity (q) given the mean and the variance of the individual productivity of groups (P_i, V_i), which were derived also for groups of operators never seen before (P'_i, V'_i), and the service level required as defined in our notation (SL). If the maximum number of operators considered cannot pick all the q items, the procedure returns the left quantity to be picked. In order to do this, we create a normally distributed variable with mean and variance given by the mean individual productivity of the group multiplied by the number of hours in a day (8h), and by the number of operators within the group. The same holds true for the variance with its rules for the linear combination. This will allow achieving the distribution of the group daily productivity for which we can calculate the cumulative density function for the required number of items picked. If this value is greater than the service level, we can state that at least LS percentage of the items will be picked by the group, and we choose this number of operators. Otherwise, we look at a greater group till the maximum number of operators that can be employed can pick the value q. If it is not feasible, the procedure provides as output for the left items to be picked. We use this procedure in our main part of the code to derive the expected number of ordinary and overtime operators (E_p, E_s). Specifically, for every class-k of picked quantities we look for the first group that can satisfies the picked quantities required with the n_op procedure. If we find a group that satisfies q in class-k, we save it in a list (Lek). Otherwise, we have to use the maximum number of operators required, calculate the left items with n_op exploiting the normal distribution and apply another time n_op with the left quantity as input. The required number of overtime operators is therefore achieved, which is stored in another list. Also considering the overtime, if there is no group that can finish the left items, we display a suggestion for increasing the maximum number of operators allowed per shift. At the end, we obtain the expected number of required operators, both ordinary and overtime, by means of the cross product between the number of operators required for each class of picked quantities and the frequencies of each respective class.

3. Case study

In this section we present the application of the research framework to a real case study coming from the fashion sector. Given the aforementioned warehousing categorisations, the warehouse taken into consideration in this research falls within the categories of distribution centres, leased warehouses and retail distribution centres. In particular, we consider only the warehouse area devoted to one of the commissioning firms. Focusing this analysis on the shoes management since they occupy about 95% of the warehouse area. The said firm provides a forecasted growth for the maximum capacity required of 141% and three possible values of the growth for the picked items per day (g_p): 30%, 40%, and 50 %. These three values correspond to three different scenarios in this case study. For the historical analysis, we take as reference a period of 380 working days that ranges from May 2019 to December 2020. In this period, we derive the picked items per day as well as the number of operators employed in the picking activities. The researchers observe a minimum number of operators of 3 (O_{min}) and a maximum of 18 (O_r). With regard to the maximum number of operators allowed for the future (O_{max}), we use three different values (25, 30, and 35) so that we consider 9 scenarios in total. Moreover, the firm requires a minimum service level (SL) of 90% (i.e., percentage of items picked per day over the total)

Table 1: Values for P_i, V_i.

i	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
P_i	168.4	131.3	125.6	159.5	139.0	131.6	126.3	118.6	121.2	119.9	107.8	110.5	104.6	114.8	124.5	110.2
V_i	50.4	56.1	48.0	36.0	69.6	55.2	52.6	40.8	30.4	39.3	35.8	38.7	24.0	40.4	23.0	27.2
$\|H_i\|$	7	8	23	31	37	47	42	51	41	24	24	16	8	8	8	5

Table 1, report the mean individual productivity per number of operators as well as their variance and the number of observations for each group.

We derive these data as described in the stage i) of the framework. It is also important to note that P_i shows a clear decreasing trend, while increasing the number of operators. This data will be used as input in the ANOVA test, which aims to confirm statistically that the mean individual productivity inter group depends on the number of operators.

The ANOVA test is unbalanced because sample sizes were different and provides a p-value of 2.9153e-04, which confirms our hypothesis. In Figure 1, we report the ANOVA boxplot.

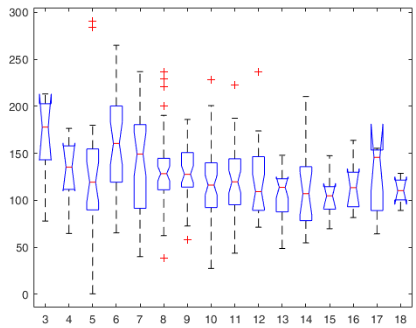

Figure 1: ANOVA boxplot for P_i.

After the ANOVA test, we carry out the fitting phase for P'_i and V'_i by benchmarking the already mentioned curves, whose results are reported in Table 2 for P'_i and in Table 3 for V'_i.

As showed in Table 2, the best fitting curve in terms of SSE is the power law with plateau. This is also consistent with the situations since increasing till infinitum the number of operators does not result in zero mean productivity but with a productivity of 68.37 $\left[\frac{units}{h*Nr\ operator}\right]$. The power law with plateau fit is reported in Figure 2.

Table 2: Parameters for the fit of P_i.

	a	b	c	SSE
$P'_i = a*i+b$	-2.80	155.4	\	1,983
$P'_i = a*i^2+b+c$	0.26	-8.22	178.30	1,644
$P'_i = a*i^b$	196.5	-0.20	\	1,648
$P'_i = a*i^b+c$	144.9	-0.43	68.47	1,638
$P'_i = a*e^{i*b}+c$	159.4	-0.02	\	1,895

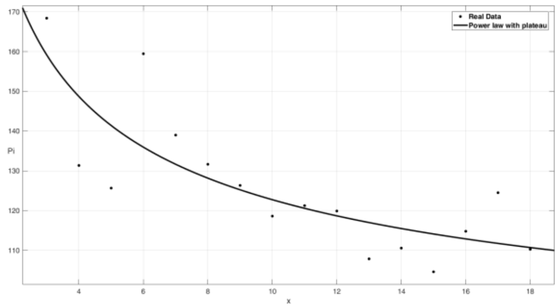

Figure 2: Power law with plateau fit for P_i.

As visible in Table 3, the best fitting curve for V'_i in terms of SSE is the power law with plateau. However, we exclude from the candidates all the curves that give a negative value for the variance with the maximum number of operators (i.e., 35). We exclude the linear and quadratic curves and also the power law with plateau because they provide variance values of -11.43, -27.78, -25.17, respectively.

Table 3: Parameters for the fit of V'_i

	a	b	c	SSE
$V'_i = a*i+b$	-2.031	59.65	\	1,350
$V'_i = a*i^2+b+c$	-0.03	-1.44	57.14	1,346
$V'_i = a*i^b$	86.07	-0.37	\	1,638
$V'_i = a*i^b+c$	-0.73	1.32	55.39	1,341
$V'_i = a*e^{i*b}+c$	64.07	-0.05	\	1,387

As with the other two fitting curves, i.e power law and negative exponential, the best in terms of SSE is the negative exponential. However, since it provides a forecasted variance for the group with 35 operators equal to 10.56, we choose the power law curve, which leads to a forecasted variance of 23.08 for the group composed by 35 operators. This choice is in line with a conservative approach that favours a forecasted variance that is more in line with the observed ones (note that a variance of 10,56 is about 50% less than the minimum observed value 23,0). After this stage, we proceed with the re-design of the current warehouse, whose layout and basic module are reported in Figure 3. This stage is not included in the framework since it heavily depends on the current warehouse characteristics, however it can be used by practicing in similar system. With respect to Figure 3: the warehouse includes 5.962 m² overall, out of which 2.446 m² are dedicated to the storage of shoes (#1), 300 m² are devoted to the storage of apparel (#2), 1600 m² are employed as a buffer (inbound and outbound) (#3), 619 m² are used as a count area (#4), 175 m² as a quality control area (#5), and the remaining 822 m² as a packaging area (#6).

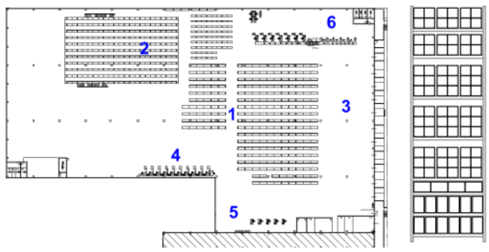

Figure 3: Warehouse layout as-is and base module.

The base module, which is used as shelving, is 2.78 meter wide and 1 meter deep. This module is organised in eight levels, where the first three are employed for the picking and the other five are used as stock. This management requires a specific procedure of goods lowering – from the stock level to the picking level- when the quantity of picking goods is not sufficient for the fulfilment of the picking orders. The 95% of the items (shoes) is managed through packages, which are contained in master boxes positioned on pallets. The average dimension of a master box is 546 mm x 620 mm x 327 mm. The capacity of a single module corresponds on average to 2,554 items (i.e., pair of shoes), after having reduced its own capacity by the 5% to be conservative. From the above mentioned data, it is possible to obtain the capacity of each single aisle as well as the overall capacity of the warehouse, corresponding to 630,739 items. This layout has been reconsidered and revaluated on the basis of the customer's growing projections/predictions. In particular, the customer foresees for the year 2025 an increase of the maximum storage capacity in the amount of 141%, compared to the current quantities. Considering the capacity of modules and aisles, it is calculated with regards to year 2025 an increase of 109,158 items of warehouse capacity, i.e. 43 new modules. Given the current layout, these new modules can be added to the already existing aisles, which will become deeper. As a conclusion, despite the maximum storage is subjected to a growth of the 141% during five years (from a maximum storage of 306,246 items to 739,897 items), the related space increase (i.e., shoes storage area) is not proportional. In particular, the area (#1) increases only by 16.27% (from 2,446 to 2,844 m²). On the contrary, the area (#2), which is related to apparel that are not the focus of this work, make use of the area not yet occupied, since that the floor area remains unchanged as shown in Figure 4.

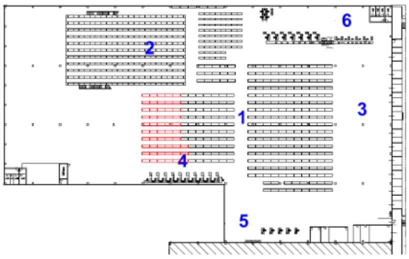

Figure 4: Warehouse layout to-be.

In conclusion, it can be stated that the current warehouse area is oversized compared to the currently managed quantities and requires a relatively small expansion compared to the forecasted growth.

We now apply our procedure to the aforementioned nine scenarios.

Table 4: Values for f_k, l_k, u_k, m_k, m'_k

f_k	l_k	u_k	m_k	$m'_k(+30\%)$	$m'_k(+40\%)$	$m'_k(+50\%)$
18%	1,756	3,192	2,474	3,216	3,463	3,711
9%	3,192	4,628	3,910	5,083	5,474	5,865
18%	4,628	6,064	5,346	6,949	7,484	8,019
12%	6,064	7,500	6,782	8,817	9,495	10,173
15%	7,500	8,936	8,218	10,684	11,506	12,328
2%	8,936	10,372	9,654	12,551	13,517	14,482
2%	10,372	11,808	11,090	14,418	15,527	16,636
9%	11,808	13,244	12,526	16,285	17,538	18,790
9%	13,244	14,680	13,962	18,152	19,548	20,944
6%	14,680	16,116	15,398	20,019	21,559	23,099

In Table 4 we report the values of the ranges in which we subdivide the picked quantities as well as their bounds and frequencies. We also report the new mean values per class (m'_k) obtained by increasing the original mean of 30-40-50%. These values, combined with the original mean individual productivity per number of operators per group and with the forecasted ones, are the inputs for proposed procedure, which leads to the results listed in Table 6 for each scenario. In Table 5 we report the manpower costs and the assumption about the working hours per day and the working days per week to get the results reported in Table 6.

Table 5: Hourly manpower costs and working days.

Hourly ordinary manpower cost [$€/h$]	30
Hourly overtime manpower cost [$€/h$]	39
Working weeks in a year [$weeks/year$]	52
Working days in a week [$days/week$]	5
Hours per day per operator [$h/days$]	8

As already stated, we assume that eight hours per day per operator are allowed and that there are five working days in a week since these are the actual working conditions. For the manpower cost we take as reference the actual hourly cost for ordinary operators and increase it by 30% for overtime operators.

Table 6: Results of the case study

	E_p	E_s	Total annual cost [$€/year$]
$m'_k(+30\%)$ and $O_{max} = 25$	15	2	1,098,240
$m'_k(+30\%)$ and $O_{max} = 30$	16	1	**1,079,520**
$m'_k(+30\%)$ and $O_{max} = 35$	17	1	1,141,920
$m'_k(+40\%)$ and $O_{max} = 25$	17	3	1,304,160
$m'_k(+40\%)$ and $O_{max} = 30$	18	2	1,285,440
$m'_k(+40\%)$ and $O_{max} = 35$	19	1	**1,266,720**
$m'_k(+50\%)$ and $O_{max} = 25$	17	4	1,385,280
$m'_k(+50\%)$ and $O_{max} = 30$	18	2	1,285,440
$m'_k(+50\%)$ and $O_{max} = 35$	19	1	**1,266,720**

As can be seen in Table 6, with a forecasted growth of the picked quantities of the 30%, the minimum annual cost is given in the scenario with the maximum number of operators equal to 30. Specifically, the number of expected ordinary operators in this optimal scenario is 16 with only one expected overtime worker. On the other side, for the forecasted growth of picked quantities both of 40% and 50%, the optimal scenario provides a maximum number of operators of 35 with an expected number of ordinary operators of 19. Also, in these cases only one overtime worker is expected. This is an interesting result that highlights how the number of operators chosen for the growth scenario of 40% is not fully exploited, and therefore this workforce can sustain an additional work of about 10%. This result allows to forecast that we can measure the workforce as in the 40% growth scenario because the operators will be able to deliver also additional works without requiring further workforce investments.

4. Conclusions

In this paper we have presented a scientific approach for the workforce resizing. Specifically, we have proposed a procedure that, thanks to its underlying simplicity, can be easily used by practitioners. The application of the proposed framework to a real case study allowed to achieve interesting findings. The mean individual productivity per group number was fitted very well by a power law with plateau confirming the freeride behaviour in these groups. In addition, the final output of the framework clearly showed how the same workforce used for a growth of the picked quantities of 40% can be used also in the case of a growth of 50% because in the first scenario the resources are not fully exploited. These findings are useful both from a tactical and from an operational viewpoint. Further works in this direction can include a simulation of such a system in order to include a division of picked quantities through the day and a subsequent differentiation of the service level based on the orders' priorities. Other extensions of this work can investigate the impact of introducing competitivity between groups to avoid the free ride behaviour.

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