JJMIE

Volume 13, Number 1, May. 2019
ISSN 1995-6665
Pages 49 - 59

Jordan Journal of Mechanical and Industrial Engineering

Integration of Benchmarking with Overall Equipment Cost Loss for Industrial Process Improvement

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Received 24 Feb. 2019

Abstract

Overall Equipment Cost Loss (OECL) can be used to calculate the cost of losses due to availability, performance and quality. However, the lack of a benchmark limits the capability of the OECL model. A data envelopment analysis model is integrated with the classical OECL model to obtain target values as benchmarks. For validation, the proposed model was implemented to a printing and packaging company. Results showed the effectiveness of the proposed model, where the OECL improved by 13.7%.

Keywords: Overall Equipment Effectiveness (OEE), Overall Equipment Cost Loss (OECL), Benchmarking, Data Envelopment Analysis (DEA);

1. Introduction

There are many different approaches to measuring manufacturing effectiveness and generally, most companies will have some measures already in place. Several studies Implemented OEE which resulted in major improvements. However, OEE and other adapted measurement are not suitable for use in some conditions; for example, when applied to compare differences in machine type, capacity and also operating cost. Therefore, many researchers attempted to improve its weaknesses **(**Islam H. Afefy 2013). OECL can sequence the problems of each machine by calculating the production loss and represents the results as the monetary unit (Wudhikarn et al. 2010).

Data envelopment analysis is a linear programming and production theory-based mathematical approach developed by (Charnes et al. 1978). A decision-making unit (DMU) is considered the element subject to comparison (Ramanathan 2003). The DEA is combined with OEE to identify at what level (target values) the modifications must be made to improve the performance of machines (Aneirson Francisco da Silva et al 2017). Mousavi-Nasab focuses on some of the difficulties that happen when the OEE or the DEA is used for allocating the resources and ranking the measures in production systems (Mousavi-Nasab et al 2019). Various benchmarking techniques are being used all throughout the world, from simple ratio to complex statistical and mathematical modeling in addition DEAP V.2 programming was utilized for technical efficiency and analysis of benchmarking (Haziq et al. 2019).

1.1. Categorisation of OEE Researches

OEE is nowadays considered as one of the most important performance metrics being used. This has prompted a wide stream of scholar research by the academic community (Mrs. Nur Ainunnazli Binti Aminuddin et al. 2016). Figure 1 shows some types of OEE and table 1 shows a number of directors published in these OEE types.

A proposal of this study is to improve the weaknesses of OECL by adopting the existing calculating methodology. OECL does not have world class to compare machines performance with the best practice so, integrated OECL with data development analysis (DEA) were proposed to overcome the weakness of this issue. In addition, a case study was conducted in the real manufacturing process for over four years to evaluate twenty pieces of machines. More specifically, the main contribution of this research is that:

It helps the decision-maker to define which machine needs improvement first that will speed up the improvement process.

Another purpose of this paper is to overcome the challenges that arise when implementing the OECL and the DEA; and

The DEA with the OECL were used whereas no research publication has considered the use of the DEA with the OECL.

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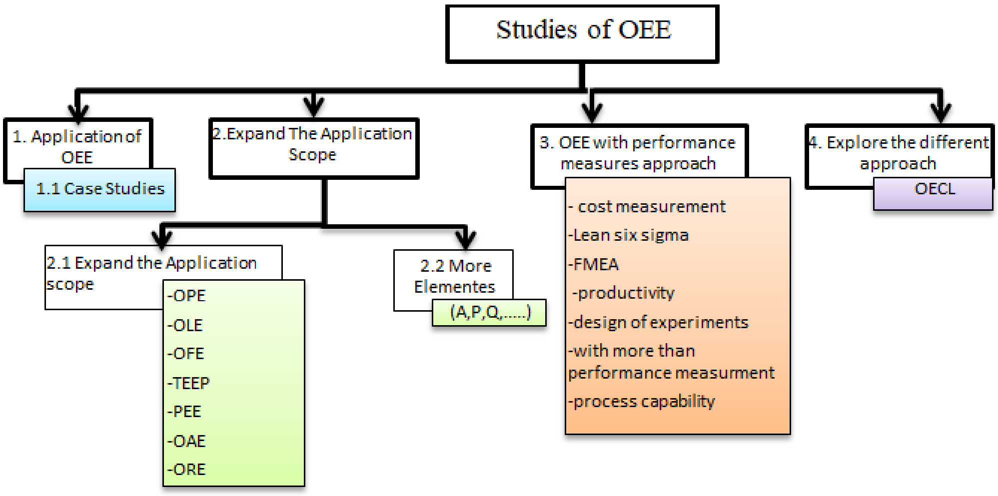

Figure1. summary shows categorization into four areas that some academic research has conducted on OEE over the last two decades.

Table 1. Summary and categorization of OEE researches.

Authors	**Ratapol Wudhikarn (2010)**	**Osama Taisir R. Almeanazel (2010)**	**Ratapol Wudhikarn (2012)**	**Ratapol Wudhikarn (late 2010)**	**Binoy Boban And Jenson Joseph (2013)**	**Dani Yuniawan et al. (2013)**	**Ratapol Wudhikarn et al. (2013)**	**Islam H. Afefy (2013)**	**Abdul Talib Bon And Mandy Lim (2015)**	**Ratapol Wudhikarn (2016)**	**N.C.Maideen ET AL. (2016)**	**M. Braglia ET AL. (2017)**	**Mihir K shah ET AL. (2017)**	**Dorota Stadnicka and Katarzyna Antosz(2018)**	**This paper**
Classic OEE		√						√			√				
Expand the application scope				√				√				√		√	
OEE with performance measures, approaches					√				√				√		√
Explore the different approach	√		√			√	√			√					√

2. METHODOLOGY

2.1. Overall Equipment Effectiveness

OEE is formulated of three components: availability, performance, and quality; it is used to determine various types of productivity losses. The major six losses to identify for calculation of OEE are: breakdowns, setup and adjustments, small stops, reduced speed, startup losses, and production losses.

$$\text{Availability rate} = \text{Operating time / planned production time} \quad (1)$$

$$\text{Performance rate} = \text{Actual production/(operation time x ideal run rate)} \quad (2)$$

$$\text{Quality rate} = \text{Good pieces / Actual production} \quad (3)$$

$$\text{OEE} = \text{Availability x Performance x Quality} \quad (4)$$

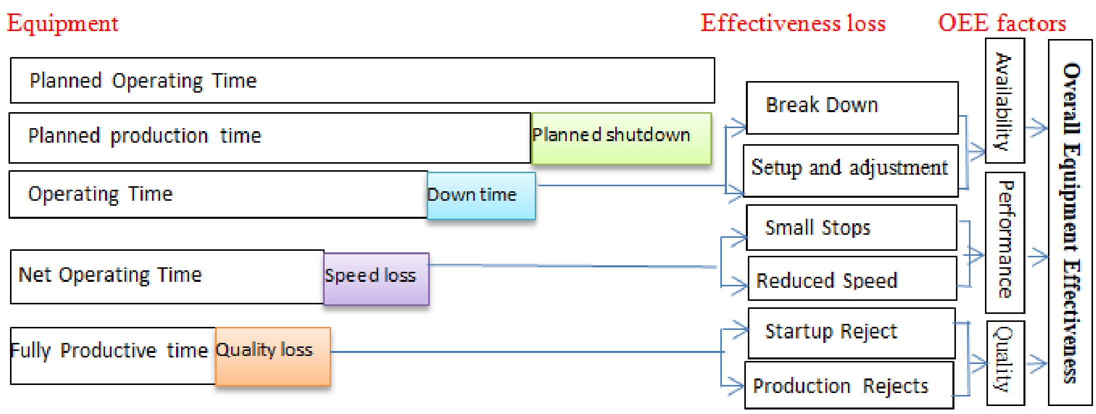

Figure 2. Overall Equipment Effectiveness calculation and losses.

2.2. Overall Equipment Cost Loss

This method analyses loss into three components following the OEE approach, but the result is shown in cost. However, losses in each component are dissimilar and depend on resource usage.

2.2.1. Availability losses

Losses calculating method for availability rate as following.

OL_{avil} = DT x IRR x PPU (5)

By, DT = breakdown time + set up and adjustment time (6)

$$PCL_{avil} = \frac{DT\ X\ EP_{avil}}{planned\ production\ time} \quad (7)$$

By, EP_{avil} = *Direct labor cost+ Indirect labor cost+ Depreciation cost+ Maintenance cost+ Renting cost + Insurance cost+ Welfare* (8)

Total losses of the availability rate element can be calculated from the following equation:

AL = OL_{avil}+ PCL_{avil} (9)

Where, OL_{avil} : Opportunity loss for availability rate (US$)
DT : Downtime (hour)
IRR : Ideal run rate (unit/hour)
PPU : Profit per unit (US$/unit)
PCL_{avil} : Production cost loss for availability rate (US$)
AL : Availability losses (US$)

2.2.2. Performance losses

Loss calculating method for performance efficiency element is computed from a number of the product that is not able to produce a maximum capacity of a machine or calculates from time used to produce loss product multiply with expense per unit.

OL_{perf} = LU x PPU (10)

By, LU = Maximum capacity - Actual production (11)

Maximum capacity = *IRR X operating time* (12)

$$PCL_{perf} = \frac{LU\ X\ EP_{perf}}{maximum\ capacity} \quad (13)$$

By, EP_{perf} = *Direct labor cost+ Indirect labor cost +Facility cost + Depreciation cost+ Maintenance cost+ Renting cost + Insurance cost+ Welfare cost* (14)

Total losses of performance efficiency element can be calculated from the following equation:

PL = OL_{perf} + PCL_{perf} (15)

where, OL_{perf} : Opportunity loss for performance efficiency ($);
LU : Loss unit (unit);
PCL_{perf} : Production cost loss for performance efficiency ($);
EP_{perf} : Expense ($ /month) for performance efficiency;
PL : Performance losses ($/month).

2.2.3. Quality losses

Loss calculating method for quality rate element can be divided into two types and consists of reject and rework losses.

- Reject losses

Produced parts which do not meet quality standards right from the first time. In the six big losses, reject parts are either produced during steady-state production (process defects) or on startup after a stop event (reduced yield).

$OL_{(Qu\text{-}rej)}$ = Rej X PPU (16)

$DML_{(Qu\text{-}rej)}$=Rej X EP_{DMC} (17)

$$PCL_{(Qu\text{-}rej)} = \frac{Rej\ X\ EP_{(Qu-rej)}}{IRR\ X\ net\ operating\ time} \quad (18)$$

By, $EP_{(Qu\text{-}rej)}$ = *Direct labor cost+ Indirect labor cost+ Depreciation cost+ Maintenance cost + Renting cost + Insurance cost+ Welfare cost + indirect material cost +facility cost (US$/month)* (19)

Total losses of quality rate component sub reject can be calculated from the following equation.

RejL = $OL_{(Qu\text{-}rej)}$ + $DML_{(Qu\text{-}rej)}$ + $PCL_{(Qu\text{-}rej)}$ (20)

Where, $OL_{(Qu\text{-}raj)}$: Opportunity loss for quality rate sub reject element ($);
Rej : Number of reject (unit);
$DML_{(Qu\text{-}rej)}$: Direct material cost loss for quality rate sub reject element ($);
$EP_{(DMC)}$: Expense of direct material cost ($/unit);
$EP_{(Qu\text{-}rej)}$: Expense for quality rate sub reject($/month).

- Rework losses

Rework refers to a product which does not conform to specifications but can be repaired.

$RwkL_{(Qu\text{-}rew)} = Rew \times EP_{(Qu\text{-}rew)}$ (21)

$PCL_{(Qu\text{-}rew)} = \dfrac{Rew\ X\ \ EP_{(Qu-rew)}}{IRR\ \ X\ net\ operating\ time}$ (22)

By, $EP_{(Qu\text{-}rew)}$ = Direct labor cost+ Indirect labor cost+ Depreciation cost+ Maintenance cost + Renting cost + Insurance cost+ Welfare cost + indirect material cost +facility cost (US$/month) (23)

Total losses of quality rate sub rework can be calculated from the following equation:

$RewL = RwkL_{(Qu\text{-}rej)} + PCL_{(Qu\text{-}rew)}$ (24)

Where, $RwkL_{(Qu\text{-}rej)}$:Rework losses ($);

Rew : Number of reworks (units);

$EP_{(Qu\text{-}rew)}$: Expense for quality rate sub rework element ($/month) ;

$EP_{(Qu\text{-}rew)}$: Expense of rework ($/unit).

Total losses of quality rate can be calculated from the following equation:

Quality losses (QL)= RejL + RewL (25)

Overall equipment cost loss can be computed by the following equation:

Overall equipment cost loss (OECL) =AL+ PL + QL (26)

2.3. Data Envelopment Analysis

DEA is a technique of analyzing the efficiency of the organization using linear programming.

2.3.1. Efficient frontier types

DEA models can be input-oriented with the purpose of reducing the number of used resources and keeping the obtained results constant, or output-oriented seeking to increase the obtained results values and keep the number of used resources constant.

2.3.2. Data Envelopment Analysis models

The DEA CCR model (Charnes et al. 1978), with constant return of scale, and DEA BCC model (Banker et al. 1984), with variable return of scale, can be used to evaluate relative efficiency of a set of homogeneous Decision-Making Units (DMUs); moreover, these DEA models do not require a specific form of the production function, and they are especially suitable for multi-input and multi-output scenarios (Ohsato and Takahashi 2015). Constant returns to scale happen while increasing the number of inputs leads to an equivalent increase in the output. If it is suspected that an increase in inputs does not result in a proportional change in the outputs, a model which allows variable returns to scale (VRS) such as the BCC model should be considered as shown in the table 2.

2.3.3. Other Data Envelopment Analysis models

If we replace $\sum\lambda = 1$, with $\sum\lambda \le 1$, then we obtain non-increasing RTS (NIRS) envelopment models. If we replace $\sum\lambda = 1$, with $\sum\lambda \ge 1$, then we obtain non-decreasing RTS (NDRS) envelopment models Somchai Pathomsiri (2006) as shown in the table 2.

Table 2. Data envelopment analysis models.

Frontier types	Input- oriented	Output-oriented
CRS	Min θ s.t. $\sum_{k\epsilon k} \lambda_k y_{km} - s_m^+ = y_{km}$, m=1,…….,M $\sum_{k\epsilon k} \lambda_k x_{kn} + s_n^- = \theta x_{kn}$, $n = 1, \dots\dots, N$ $\lambda_k \ge 0$, k=1,……,K	Max Φ s.t. $\sum_{k\epsilon k} \lambda_k y_{km} - s_m^+ = \Phi y_{km}$, m=1,………., M $\sum_{k\epsilon k} \lambda_k x_{kn} + s_n^- = x_{kn}$, $n = 1, \dots\dots, N$ $\lambda_k \ge 0$, k=1,……,K
VRS	Add $\sum_{k\epsilon k} \lambda_k = 1$	
NIRS	Add $\sum_{k\epsilon k} \lambda_k \le 1$	
NDRS	Add $\sum_{k\epsilon k} \lambda_k \ge 1$	
Efficient target	$\hat{x}_{kn} = \theta\, x_{kn} - s_n^-$, $n = 1, \dots\dots, N$ $\hat{y}_{km} = y_{km} + s_m^+$, $m = 1, \dots\dots, M$	$\hat{x}_{kn} = x_{kn} - s_n^-$, $n = 1, \dots\dots, N$ $\hat{y}_{km} = \Phi y_{km} + s_m^+$, $m = 1, \dots\dots, M$

Where,

k : number of DMU being compared in the DEA analysis

θ: the input efficiency score of the DMU being evaluated by DEA

Φ : the output efficiency score

y_{km} : amount of output

x_{kn} : amount of input

n: number of inputs used by the DMU

m : number of outputs generated by the DMU

sm+ : output slacks

sn^- input slacks

λ : Vector of constants

3. CASE STUDY

The case study was conducted in the printing and packaging industry in Egypt. Management level planned to adopt a TPM system in the near future. The work runs either in one shift or in two shifts depending upon the workload. Machines from 1 to 7 are in the printing department and machines from 8 to 20 are in the packaging department.

The objective of this case study:

- To compare OEE of printing and packaging section with ideal/world class OEE.
- To analyze how companies apply OEE and OECL to monitor losses.
- To suggest the ways to implement OECL and DEA in printing and packaging plant.

3.1. Data Collection

OEE and OECL for three years have been measured from 2014 to 2016 of the twenty machines.

3.2. Monthly OEE Calculation

OEE has been calculated for a particular machine (1) of type 6 color printing machines in January 2014 as shown in the table 3. The same calculations were done for the rest of the machines.

3.3. Monthly OECL Calculation

Table 4. Calculation of OECL before the implementation of improvement in the machine (1).

Table 3. Calculation of OEE before the implementation of improvement in the machine (1).

Production data				
Planned production time (hr)	401	;	Down time (hr) 1111139hhh(((hrtime(L'	139
Ideal run rate (sheet/hr) sheet/hour	10,000	;	Target production (unit) (unit)	2,621,000
Actual production (unit)	1,207,181	;	Defect (unit)	1,286
Support variable	**Calculation**			**Result**
	operating time (hr)lanned production time - downtime loss			262
	Good pieces (unit)actual production – defect			1,205,895
OEE Factor	**Calculation**			**Result**
Availability (%)	operating time / planned production time			65.36
Performance (%)	actual production/(operation time× ideal run rate)			46.06
Quality (%)	good pieces / actual production			99.89
Overall OEE (%)	availability × performance × quality			30.07
OEE Factor	**World class**			**OEE (Case study)**
Availability (%)	90			65.36
Performance (%)	95			46.06
Quality (%)	99.9			99.89
Overall OEE (%)	85			30.07

Table 4. Calculation of OECL before the implementation of improvement in the machine (1).

Cost data				
Paper cost (L.E/ unit)	1.60	;	Labor cost (L.E)	23,510.50
Material cost (L.E/unit)	1.95	;	Maintenance Cost (L.E)	15,116.87
Profit per unit (L.E/unit)	0.60	;	Facility Cost (L.E)	20,314.77
We assumed depreciation, renting, insurance, welfare and rework cost = zero				
Losses in availability	**Calculation**			**Result**
OL_{avil} (L.E)	LT X IRR X PPU			833400
PCL_{avil} (L.E)	DT x(Labor cost + Maintenance Cost)/ planned production time			13379.90
Losses in performance	**Calculation**			**Result**
LU (unit)	Maximum capacity - Actual production			1,413,819
OL_{perf} (L.E) (L.E)	LU *X* PPU			848291.4
PCL_{perf} (L.E) (L.E)	LU×(Labor cost + Maintenance Cost+ Facility Cost) /(operating time × IRR)			31794.6
Losses in quality	**Calculation**			**Result**
$OL_{(Qu-rej)}$ (L.E)	Rej X PPU			771.4
$DML_{(Qu-rej)}$ (L.E)	Rej X EP_{DMC}			2507.0
$PCL_{(Qu-rej)}$ (L.E)	Rej×(Labor cost + Maintenance Cost+ Facility Cost) /(net operating time × IRR)			62.77
Reject losses (L.E)	$OL_{(Qu-rej)}$ + $DML_{(Qu-rej)}$ + $PCL_{(Qu-rej)}$			3341.2
Rework losses (L.E)				0
OECL factor	**Calculation**			**Result**
Availability Loss(L.E)	OL_{avil} + PCL_{avil}			846,780
Performance loss (L.E)	OL_{perf} + PCL_{perf}			880,085.95
Quality loss (L.E)	RejL + RewL			3341.2
OECL (L.E)	AL+ PL+ QL			1,730,207.03

3.4. Data Envelopment Analysis Model

For empirical analysis, we use DEAP 2.1 programming (A Data Envelopment Analysis Computer Program), which was composed by Tim Coelli (Coelli, T 1996). The DEA method is suitable in the printing sector because it can easily handle multiple inputs-outputs producers and it does not require the specification of an explicit functional form for the production frontier or an explicit statistical distribution for the inefficiency terms, unlike the econometric methods. Machines efficiency has been estimated using the DEA models, an output-oriented model with constant returns to scale. The input considered in the model (downtime, loss units, defect) and The output considered in the model (availability loss, performance loss, quality loss). Printing machines have been classified into three groups. These are based on the fact that it has the same capacity and type. The first group includes (machine 1 and 2), The second group includes (machine 3 and 4), the third group includes (machine 6 and 7). For group 1, we considered 24 DMU associated with the monthly production of two printing machines from January to December 2016. Thus, the twenty-four first DMUs correspond to machine (1), while the following 12 DMUs correspond to machine (2).

3.4.1. Data preparation and normalization

In a typical DEA model, the minimum number of DMUs required is the maximum of sum and product rules, which are shown in Eq. (27), where n_{input} is the number of inputs and n_{output} is the number of outputs (Ramanathan, 2003).For the current model, the minimum number of DMUs required is 18 (max {(3 × (3 + 3) = 18 ; 3 × 3 = 9}).

The number of DMUs $\geq$ max{3 $(n_{input} + n_{output})$, $(n_{input} \times n_{output})$} (27)

Availability losses, performance losses, quality losses are transformed into thier inverse to be able to satisfy the maximization objective of the proposed DEA model.

Finally, the prepared data is normalized by using the mean normalization method. Since there is an imbalance in the data magnitude due to multiple units such as million pound and hours, the mean normalization procedure has been applied for all of the inputs and the output. This normalization method is widely used in previous DEA studies (Gokhan Egilmez, Deborah McAvoy 2013). Mean normalization was simply conducted by calculating the mean for each input and output and dividing each input or output by its respective mean.

In table 5, anyone can verify that machine (1) is the most critical because among the first 12 DMUs (highlighted in bold letters in table 5 in the efficiency ranking, twelve are related to machine (2).

Table 5. Efficiency ranking, the target value for DMUs.

DMUs	Target value			Efficiency
	AL	pL	QL	
1	64,132.72	19,132.17	208.65	0.051
2	71,187.15	22,722.85	229.70	0.067
3	75,586.92	23,800.14	244.30	0.075
4	87,195.63	26,967.90	282.42	0.098
5	82,994.51	22,366.25	273.75	0.076
6	128,224.81	24,884.85	447.74	0.123
7	56,180.10	17,132.42	182.28	0.04
8	85,007.50	24,415.19	277.95	0.085
9	79,678.32	19,982.39	265.62	0.064
10	67,983.16	17,355.19	226.03	0.048
11	56,564.76	17,330.15	183.42	0.041
12	52,521.02	16,437.48	169.88	0.036
13	140,655.22	42,286.10	457.16	0.244
14	165,159.41	49,843.45	536.50	0.338
15	295,047.90	64,335.04	1,007.01	0.725
16	152,011.16	46,456.30	493.14	0.289
17	220,722.86	58,150.69	730.49	0.512
18	831,223.26	48,007.94	5,749.28	1
19	142,562.33	40,848.14	466.25	0.239
20	144,625.13	46,366.64	466.45	0.275
21	267,551.70	67,811.21	890.62	0.725
22	142,738.27	40,611.40	467.24	0.237
23	164,722.57	45,341.55	541.72	0.303
24	281,506.07	91,199.46	906.86	1

4. RESULTS AND DISCUSSION

The comparative scenario of average OEE and total OECL values for the years (2014, 2015, 2016) are exhibited in table 6. The ranking obtained using the OEE approach is very different from that obtained using the OECL approach. According to the OECL method, machine M1 should be the first to be improved, whereas the OEE results suggest almost the opposite: m1 is ranked seventh for improvement according to the OEE methodology. This difference is caused by the two different methodologies approaches to the consideration of incurred losses. This outcome is not surprising. OEE is not directly correlated to OECL because the relationship between the two depends on several factors related to machine capacity, the prices of product and production cost (Wudhikarn et al. (2010). Therefore, OEE and OECL results can differ. These results are consistent with the ratings of OECL in the table 5 **in** which, the machine (1) is worse than the machine (2).

The total loss in the printing department is greater than the sum of the loss in the packaging section. For this, the printing department has priority in finding the reasons for increasing the cost of losses. In addition, M1 needs to improve first (see figure 3).

4.1. Regression Analysis

Table 7 shows that the observed p-value are less than 0.05 for AL, PL, and QL. The main factor affecting machine's (1) OECL is availability loss, it was the least value for p-value.

Table 6. Machine criticality by OEE and OECL method.

Machine NO.	OEE (%)	OECL (L.E)	Ranking by	
			OEE	OECL
m1	36.9	60,542,413.69	7	1
m2	44.3	32,867,737.57	12	4
m3	43.2	39,993,744.47	11	3
m4	38.5	47,807,772.68	8	2
m5	32.7	9,148,268.20	6	7
m6	28.8	16,195,022.13	5	5
m7	40.8	15,644,594.17	9	6
m8	20.0	3,547,780.61	2	17
m9	19.7	5,049,524.81	1	15
m10	26.7	10,633,101.60	4	10
m11	60.7	3,087,309.14	16	20
m12	40.9	5,300,603.72	10	14
m13	45.1	9,382,783.34	13	11
m14	64.9	4,337,783.45	17	16
m15	25.0	3,482,153.58	3	9
m16	45.4	6,389,608.43	14	13
m17	58.2	3,386,346.78	15	19
m18	64.9	7,489,973.30	18	12
m19	71.0	14,535,237.39	20	9
m20	69.1	20,333,034.30	19	8

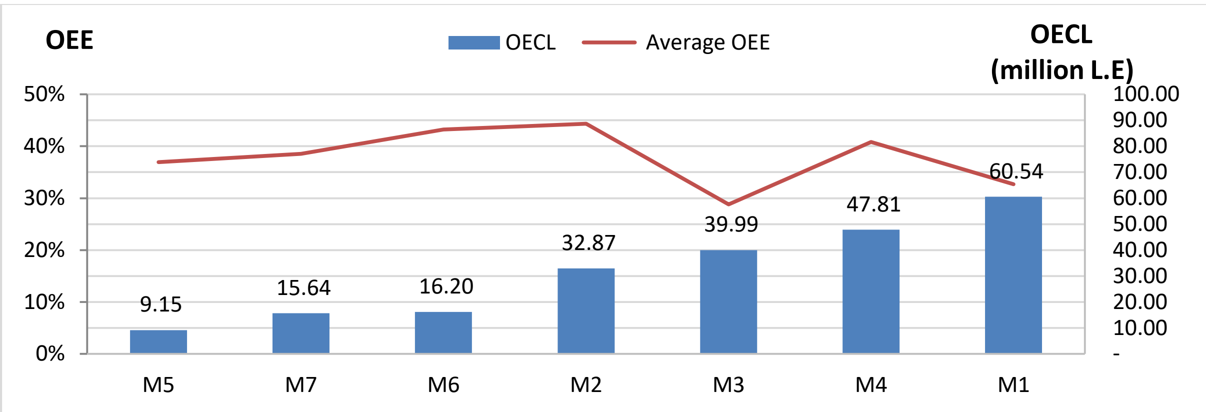

Figure 3. comparing between average OEE and total loss for printing machine at 2014, 2015 and

Table 7. Variables and its significance value (p).

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	7.37E-11	1.88E-10	0.392521	0.704924	-3.6E-10	5.06E-10	-3.6E-10	5.06E-10
AL(x1)	1	1.5E-16	6.65E+15	2.9E-124	1	1	1	1
PL(x2)	1	5.16E-16	1.94E+15	5.6E-120	1	1	1	1
QL(x3)	1	9.71E-15	1.03E+14	8.8E-110	1	1	1	1

4.2. Downtime Analysis with Pareto Analysis

Pareto diagram was drawn. It has been obtained that Blanket cylinder cleaning has caused around 22% of the total downtime whereas, no job was unavoidable. Maintenance, set up, end week cleaning and waiting for the paper were next prioritizing downtime factors. Cumulative percentage of downtime has been measured and shown in figure 4 below.

4.3. Implementation of Improvement

For availability improvement of the machine (1), downtime problems were identified and the following remedies have been suggested in order to improve the effectiveness as shown in table 8.

4.4. Calculation OECL After Improvement

After improvement is applicated, OECL is measured one more time in 2017. OECL results for the machine (1) did not reach the target value but it showed a marked improvement as shown in the table 9.

It can be seen that OECL on the printing section has shown a marked decline, which is an indication of a decrease in equipment availability losses, a decrease in quality losses, and a decrease in performance losses as shown in figure 5.

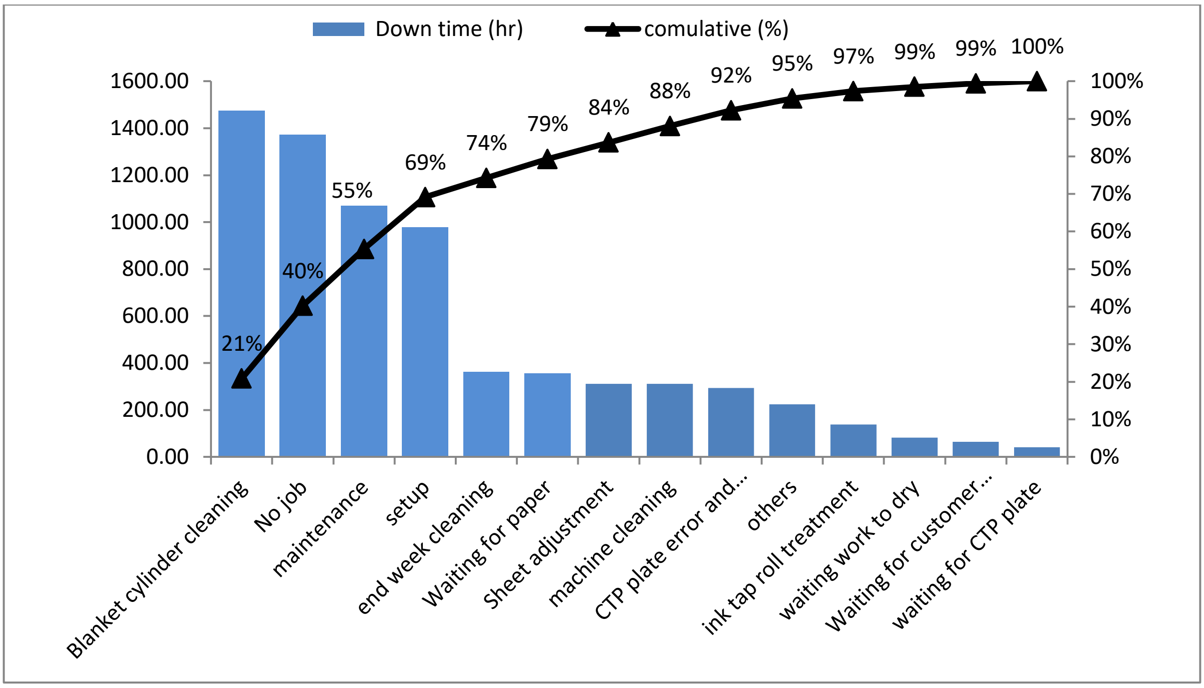

Figure 4. Pareto chart for the machine (1) at 2014, 2015 and 2016.

Table 8. Shows abnormality, causes, and recommendation.

Abnormality	Causes	Recommendation
Blanket cylinder cleaning	- Ink drying on the press. - The unground pigment or foreign matter in ink. - Worn blanket ; particles coming out of the blanket surface. - Loose dust particles on the paper surface - bits of coating/fiber is pulled from the paper's surface.	- Adjust to proper ink/water balance - Consult the ink manufacturer and request change - Treat blanket or change it - wipe papers with glycerine or tack cloth - Contact paper supplier.
No job	- Low demand - Poor marketing	- It cannot be controlled because it depends on demand.
Set up	- More job changeover time	- SMED
Corrective maintenance	- poor equipment condition - There is no maintenance plan for failures before they occur.	- Preventive maintenance as part of planned maintenance
End week cleaning	- Beginning in the weekly cleaning early.	- Delay the cleaning until the end of the Production.
Wait for paper	- The lack of information distributed to sections (production and planning and warehouses and design and quality).	- Use Smart planning tool (material and inventory management) - Improve access to information.

Table 9. Calculation of OECL after implementation of improvement techniques in the machine (1) at 2017.

Cost data			
Paper cost (L.E/unit)	1.60	Labor cost (L.E)	23,510.50
Material cost (L.E/unit)	1.95	Maintenance Cost (L.E) ((L.E)	12,954.05
Profit per unit (L.E/unit)	0.60	Facility Cost (L.E)	17,293.82
We assumed depreciation renting, insurance, welfare and rework cost = zero			
Production data			
Planned production time (hr)	349 ;	Down time (hr) 1111139hhh(((hrtime(LT)	184.95
Ideal run rate (sheet/hr) sheet/hour	10,000 ;	Target production (unit) (unit)	1,640,500
Actual production (unit)	1,211,504 ;	Defect (unit)	1,250
Net operating (hr)	11103		
Support variable	**Calculation**		**Result**
operating time (hr)	planned production time - downtime loss		164.05
Good pieces (unit)	actual production – defect		1,210,254
OL_{avil} (L.E)	DT X IRR X PPU		1,109,700
PCL avil (L.E)	DT x(Labor cost + Maintenance Cost)/ planned production time		19324.1
Losses In Performance	**Calculation**		**Result**
LU (unit)	Maximum capacity - Actual production		428,996
OL_{perf} (L.E)	LU *X* PPU		257397.74
perf (L.E)	LU×(Labor cost + Maintenance Cost+ Facility Cost)/ (operating time × IRR)		14058
Losses in quality	**Calculation**		**Result**
$OL_{(Qu\text{-}rej)}$ (L.E)	Rej X PPU		750.0
$DML_{(Qu\text{-}rej)}$ (L.E)	Rej X EP_{DMC}		2437.5
$PCL_{(Qu\text{-}rej)}$ (L.E)	reject×(Labor cost + Maintenance Cost+ Facility Cost) /(IRR × net operating)		55.47
Reject losses (L.E)	$OL_{(Qu\text{-}rej)}$ + $DML_{(Qu\text{-}rej)}$ + $PCL_{(Qu\text{-}rej)}$		3243
Rework (L.E)			0
(L.E)losses(L.E)			
OECL factor	**Calculation**		**Result**
Availability Loss (L.E)	OL_{avil} + PCL_{avil}		1,129,024.12
Performance loss (L.E) (L.E)	OL_{perf} + PCL_{perf}		271,455.74
Quality loss (L.E)	RejL + RewL		3243.0
OECL (L.E)	AL+ PL+ QL		1,403,722.82
OECL Factor	**Benchmark**		**OECL (Case study)**
Availability Loss (L.E)	64,132.72		1,129,024.12
Performance loss (L.E)	19,132.17		271,455.74
Quality loss (L.E)	208.65		3243
OECL (L.E)			1,403,722.82

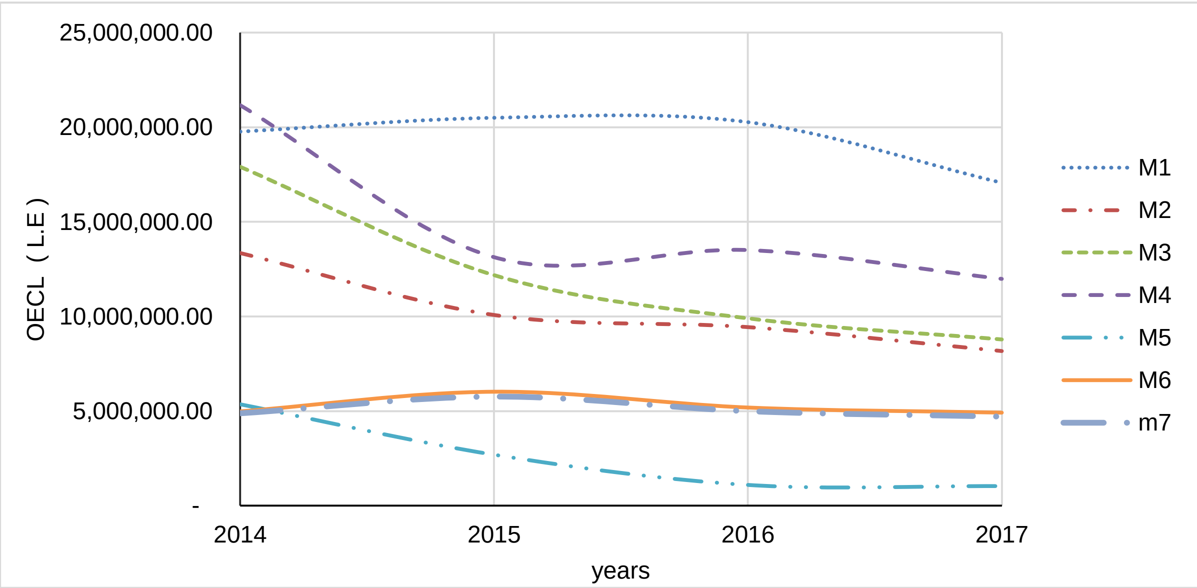

Figure 5. Improvement of OECL from 2014 to 2017.

4.5. Comparison Between OECL for the Machine (1) and Machine (2)

The machine (2)is better than the machine (1) because it is less in cost (availability losses, performance losses and quality losses), as shown in figures 6, 7 and 8, In addition, machine (2) reaches the target values in few months at 2017.

4.6. Comparison Between Target Values and OECL for the Machine (1)

It can be observed that after the application of tools improvement, each of the three factors contributing to OECL has improved and has improved OECL as a whole.the OECL of the machine (1) decreased from 19,770,543.19 to 17,066,713.84, the availability losses of the machine has been decreased from 10,746,313.83 to 13,190,441.11, performance losses from 8,975,092. to 3,825,295.10 and quality loss from 49,136.63 to 50,977.63 then OECL at 2017 have been compared with target values. OECL results for the machine (1) did not reach the target value, but it showed a marked improvement.

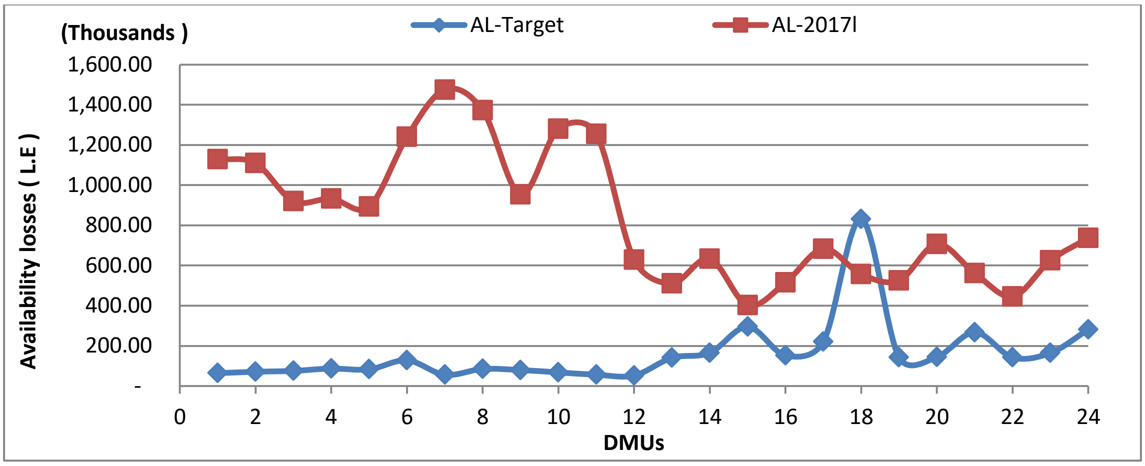

Figure 6. Target values recommended by DEA and AL in 2017 for M1 and M2.

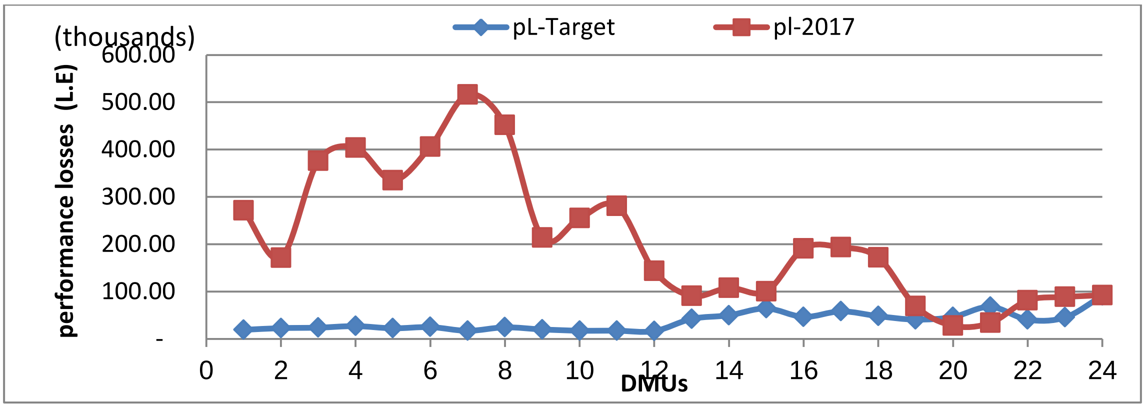

Figure 7. Target values recommended by DEA and PL in 2017 for M1 and M2.

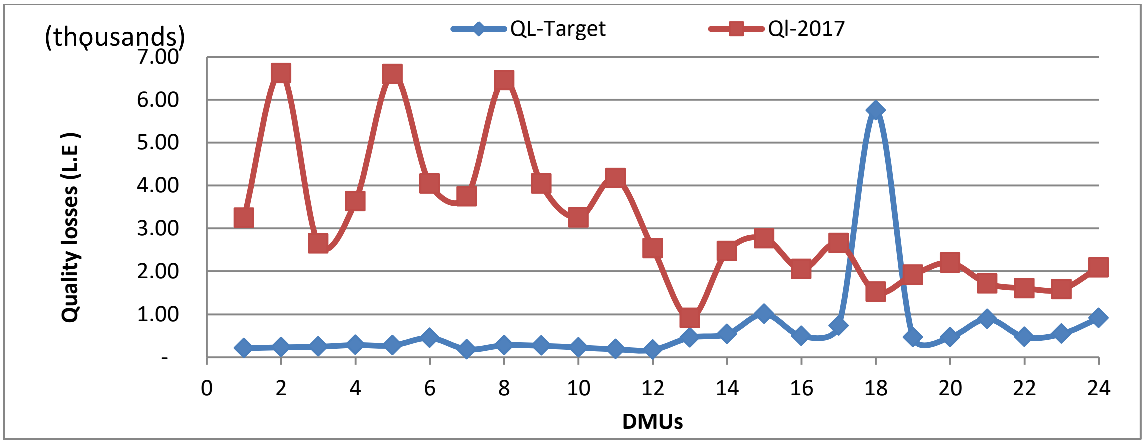

Figure 8. Target values recommended by DEA and QL in 2017 for M1 and M2.

5. CONCLUSION

The goal of this study is to assess and benchmark the OECL of printing machines, so DEA is utilized to obtain the target values. OECL and OEE for three years have been measured from 2014 to 2016. These measurements are based on the initial situation of the facility then, data envelopment analysis has been used in metric benchmarking of OECL. Regression analysis was used to examine the factors that impact OECL. Pareto analysis of downtime was performed to show the most affecting downtime factors hierarchically. After discovering the main reason for downtime, a set of procedures were carried out to improve the machines. After that, the OECL was measured again and compared to the benchmark. The machine (1) did not reach the target values, but it achieved significant improvement while some other machines reached the target value in some periods.

For future research:

It is proposed to conduct analyses with DEA models expecting a variable return to scale (DEA-BCC model). In conclusion, it is worth mentioning that the results should not be generalized to all industries, yet further tests including different areas, sectors, and products, besides expanding the number of DMUs, inputs, and outputs are required.

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