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COST ANALYSIS STUDY THROUGH OPTIMIZATION OF A SLUDGE DRYING PLANT FOR A PETROLEUM REFINERY

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ABSTRACT

A Sludge Drying Plant (SDP) produces bio-sludge cakes as end products. In most cases, it is the final processing facility of Effluent Treatment System (ETS) before it is sent out for final disposal, either through landfill or handing it over to a third party body with some economic impacts. Efficiency of the SDP determines the economic impact should this bio-sludge is handed over to a third party body for disposal. The resultant of the dry solid produced from the SDP can also tremendously affect the overall process costs. In an ideal state, the dry solid produces contain 0% water content; however, in an actual plant 0% water content can never be achieved. On disposal, Kualiti Alam, a body appointed for disposal purposes, will charge the dried cake sludge based on the weight, regardless water or dry solids. Therefore it is only sensible to export the dried cake at maximum dryness. Suitable sludge management which includes preventive maintenance and operating costs can reduce the overall process costs. This paper focuses on how cost and sludge management correlates and improvement is practically seen on an actual implementation of this optimization. Factors that contributes to the overall SDP performance for parameter optimization for the SDP is identified through actual process data a capture from a life SDP plant and analysis as well as identification of the subsystems within the SDP itself.

Keywords: sludge drying plant, process design, parameter optimization, effluent treatment system, sludge management.

INTRODUCTION

A typical output of an oil and gas or other similar facility processing plant is normally sent to a water treatment unit namely, the Effluent Treatment System (ETS). Other industries may also refer the ETS as Water Treatment Facility, which treats process discharge before being disposed into the sea, unused sludge as landfill or through a government controlled body for disposal (A.Bhardwaj *et al*., 1993). The output of the ETS itself, which may also be referred as bio-sludge is sent to the Sludge Drying Plant (SDP) in which it will perform the final processing on a wet sludge to produce a dry cake like product. This cake is then sent for disposal through the government controlled body with a cost incurred onto the industry. Industries' inability to sustain the low processing cost to produce dry solid for disposal is a major concern to some oil and gas industry and in turn reflects the currently un-optimized processing which has a high financial implication. In an ideal case for SDP with all the series of processes are at optimum level of operating, the weight ton (wt%) may reach as high as 90wt% with minimum processing cost. Other industries have already applied parameter optimization and have significantly showed a high impact on finance (Thomas E.Kissell, 2000). The ETS units operation is shown in Table-1. The typical overall ETS process flow is shown in Figure-1.

Table-1. ETS units operation.

STAGE	UNIT OPERATION	FUNCTION
EFFLUENT DISCHARGE UNIT	▪ Guard Basin ▪ Inspection Basin	▪ Final discharge point ▪ Spot for authority/DOE sampling
SLUDGE HANDLING SYSTEM	▪ Sludge Thickener ▪ Sludge Collection Tank ▪ Filter Press Unit ▪ Sludge Air Dryer	▪ Solids/sludge dewatering facilities ▪ Removal of water from sludge reducing volume for final disposal ▪ Final disposal to Kualiti Alam (KA)
OIL RECOVERY UNIT	▪ Slop Oil Recovery Vessel	▪ Collection of slop oil recovered from ETS system i.e. CPI, OWS/Ballast Storage Tank, Flow Composition Tank
INFLUENT COLLECTION SYSTEM	▪ OS/OW Lift Stations / Run Off Basin ▪ OS Storm Basins (Low/High Level Area) ▪ OW Storage Tank (Ex-Ballast Tank)	▪ Retention of effluent from various refinery sources ▪ Separates OS/OW effluent

COST EFFICIENCY AND PARAMETER OPTIMIZATION

To have a cost efficient SDP, tweaks are required on the overall system (P. A. Miderman, *et al.*, 1993). Thus, in order to establish an optimum system for cost efficient purposes, optimization is required. To make this possible, system optimization requires understanding on the type of process and medium that the system is managing (B. G. Liptak, 2006). As much data is required to determine the current performance in order to achieve a successful parameter optimization on a complex process such as the SDP (S. A. Rounds, 2002). Data collection for optimization is obtained on each step of the SDP process, which is summarized in Figure-2. Optimization may include defining the best measurement range for the

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sensors whereby each of the sensors and equipment is analyzed and compared with the targeted operating parameter to reach 90wt% optimization.

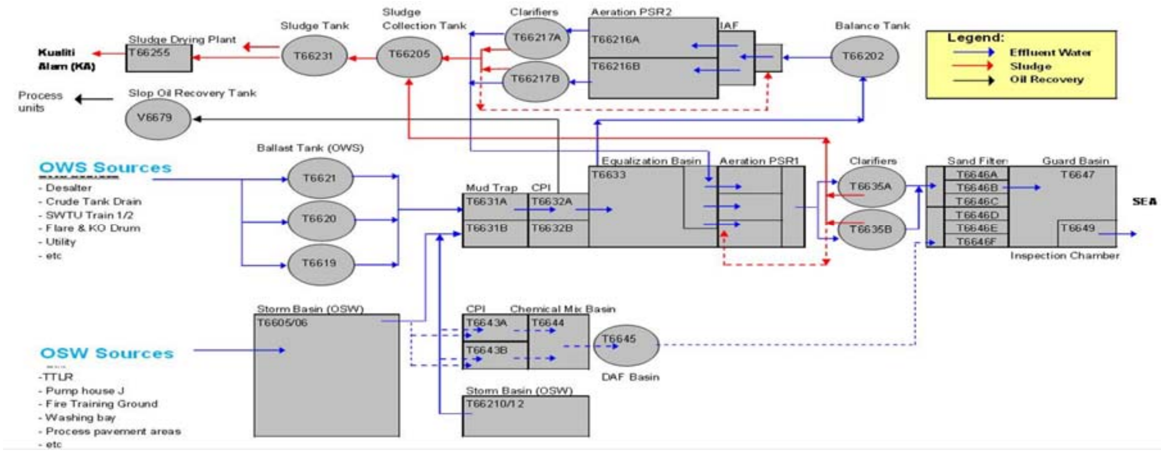

Figure-1. Overall ETS process flow.

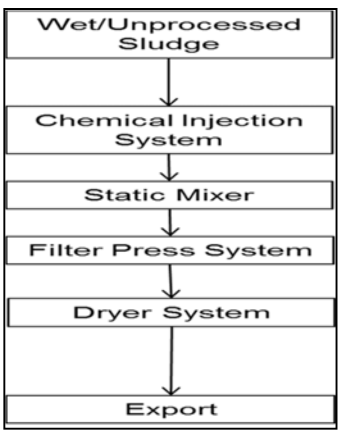

Figure-2. Stage in SDP process.

The optimization method of this study is not purely on paper. A pilot study has been conducted and actual data collection has been taken to estimate the current deviation from target, shown in Table-2. To ensure consistency and accuracy, these data are taken on random intervals to expand the variations on the sample properties during different batches of operations. The observed dry solid from the SDP, solid weight and flow rate are benchmarked against the desired output. Based on the current operating results, the calculated deviation from the target ranges from 45.7% to 52.7%, which is a gap of 7% of inconsistency. On this normal process the percentage of dry solid only reaches up to 35% dry solid compared to a target of 90% dry solid.

Table-2. Data collection on Pilot study.

Dry solid (%)	**Solid weight** (Ton)	**Flow rate** (m^3/hr)	**Deviation from target** (%)
25	0.47	2.4	52.3
27	0.45	2.7	48.7
30	0.44	2.1	52.3
29	0.46	2.2	50.7
35	0.45	2.6	45.7

a. Only showing a few number of data for paper reference.

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OPERATING COST ESTIMATES

The parameter for optimization that contributes to the highest processing cost is summarized in Table-3. The elements taken into considerations are the flow rate and pressure of the bio-sludge going in and out of the SDP, the chemical reaction and consumption, pumping efficiency, homogenous mixer operations, polymer feeder operation, filter press system and finally the logic controller itself. Quantified Element in the table describes the details on how each element can be quantified to determine the cost estimates.

Table-3. Data collection for parameter optimization and cost estimates.

Observed parameters	Quantified element
Flow rate and pressure	Time is quantified as in volume/time
Chemical Utilization	Volume of chemical usage of batch per usage.
Polymer feeder operation	Polymer volume usage is quantified.
Filter press system	Time is to process per batch is quantified.
Diaphragm pump operation	Volume transferred per batch is quantified.
Programmable logic controller	Time is quantified for process per cycle.

Figure-3 is showing a detailed optimization on the SDP elements that is then further translated into operating cost. This method is indeed more accurate as the overall system has been divided in sub-systems, which each sub-system is analyzed for its performance. Each of the subsystem optimization is then reviewed thoroughly to ensure that the cost reflects the actual performance. Also as seen Figure 3, the non-optimized elements are mainly due to mechanical movement and limitations. An example of elements that is optimized is shown in Table-4. The percentage optimization is then translated into cost.

Table-4. Optimization of parameters.

No	Action Sequence	Cycle time	Optimized Cycle Time	Optimization %
1	Close filter press	4 minutes	4 minutes	
2	Feed	120 minutes (approx.)	80 minutes (approx.)	33%
3	Inflate membranes	2 minutes	1min 45 secs	12.5%
4	Squeezing	80 minutes	60 minutes	25%
5	Deflate membranes	2 minutes	2 minutes	
6	Open filter press	2 minutes	2 minutes	
7	Discharge cakes	30 minutes	30 minutes	
	Total cycle time	4 hours	2.98 hours	70.5% Optimized

Table-5 shows the cost efficient through optimization of the SDP process, where the cost of water is reduced from $1.8m to below $500k. Pilot study showed there is correlation between system overall performance and the cost effectiveness on the operation and it is proven through actual implementation of this optimization on a live running SDP. Analysis also showed that the current efficiency of the overall system is only 50% efficient on average, which is indeed considered as poor performance by the SDP system.

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Table-5. Cost Efficiency through optimization.

	Ideal case (100% solid)	**Current operating output (25% solid)**
Ideal weight (per month)	56 Tons	56 Tons
Selling price	$2700 per Ton	$2700 per Ton
Cost incurred for solid (per year)	$1,814,400	$453,600
Cost incurred for water (per year)	$0	$1,360,800

Results from the pilot study showed that this process is nonlinear due to different product specifications per process batch, thus in order too close the gap of 40% optimization, the system has got to be divided down to sub-systems, where each sub-system is then gauged for the performance and tweaked. The non-optimized elements are improved as shown in Figure-3. As seen in Table-6, the total cost incurred on water before system optimization is $1, 360, 800, in which only 25% of the system is fully utilized for solid disposal.

Upon optimization on the actual implementation on the operating output, 90% solid content can be achieved which only $181, 440 is spent on water disposal. In an ideal case, the system can produce up to 100% solid content with $0 spent on water disposal. However, the author believes that it is not practical to achieve actual optimization performance up to ideal target.

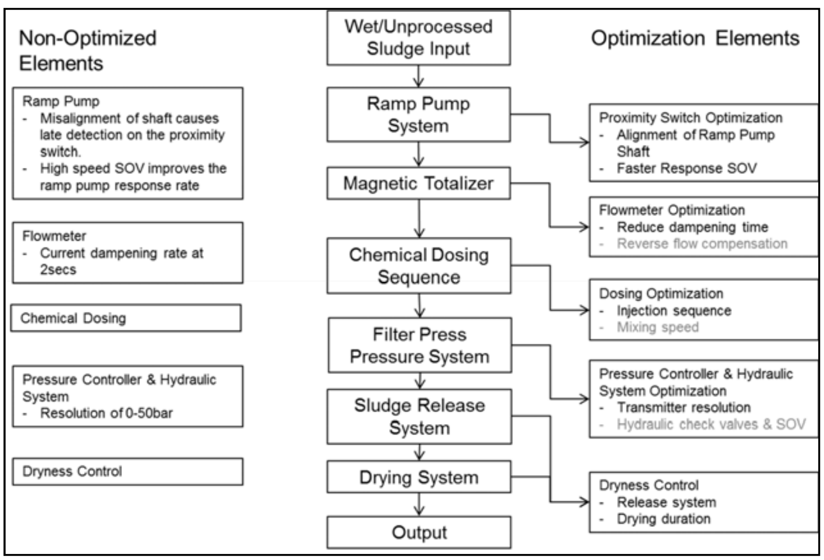

Figure-3. Non-optimized elements and optimized elements.

Table-6. Cost efficiency through optimization At 90% system efficiency.

	Ideal case (100% solid)	**Current operating output (25% solid)**	**Optimized operating output (90% solid)**
Ideal weight (per month)	56 Tons	56 Tons	56 Tons
Selling price	$2700 per Ton	$2700 per Ton	$2700 per Ton
Cost incurred for solid (per year)	$1,814,400	$453,600	$1,632,960
Cost incurred for water (per year)	$0	$1,360,800	$181,440

ALTERNATE APPROACH FOR OPTIMIZATION

On the other hand, another method of optimization on the process can also be achieved through a model based control strategy that can be implemented as this nonlinear process can be optimized through Artificial Neural Network (ANN) (A. Degani, *et al.*, 2001). To adopt and utilize ANN optimization on SDP's process, the processes executed has been distinguished and treated as separate subsystem during performance gap identification but treated as a whole during ANN implementation. Due to process nonlinearity and inconsistent repeatability, the process optimization can be visualized through ANN shown in Figure-4 (Han Chunji, *et al.*, 2009).

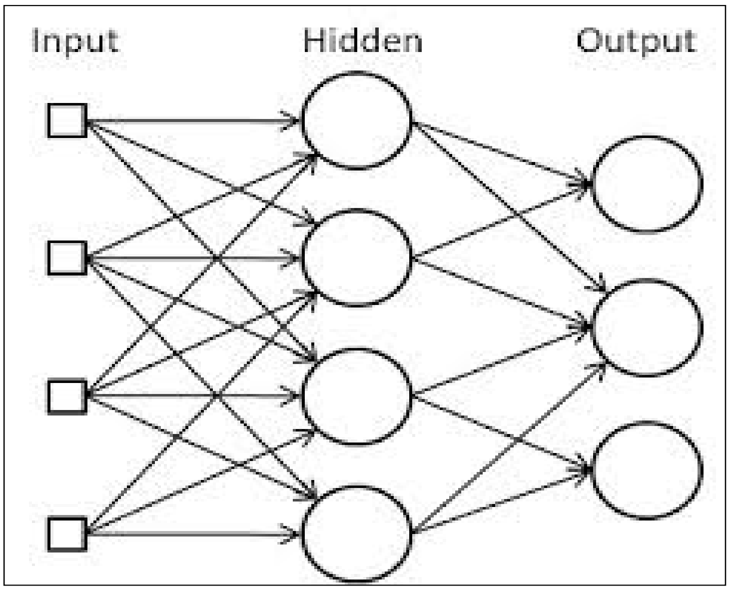

Figure-4. A Brief visualization of the ANN topology.

Similar to the optimization mentioned earlier in this paper, the identified subsystems on the SDP are the main programmable logic controller (PLC) that controls the overall process sequence, the chemical dosing system as the coagulate agent, and the non-fuel dryer system. On parameter optimization for all these subsystems, the SDP will produce up to 90wt% solid content.

The parameters on the input layer of the neural network must be a crisp representative of the processes in order to achieve the desired output (D. C. Psichogios, *et al.*, 1991). Figure-5 is visualization on the ANN to be implemented (B. Lennox, *et al.*, 2001). Author is emphasizing that ANN is also a possible method of optimization. ANN implementation onto this live system is currently being taken into considerations by the management for approval both technically and economically.

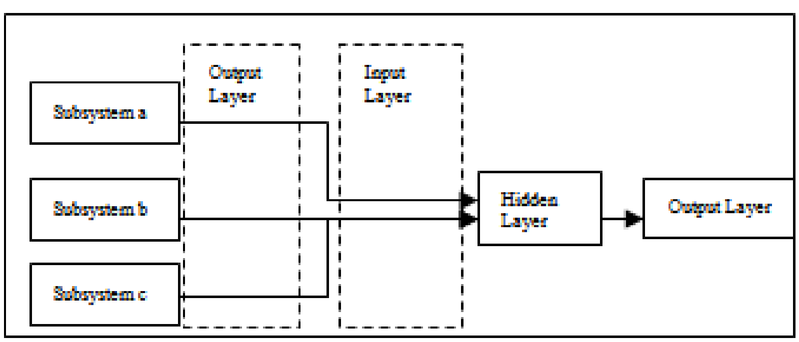

Figure-5. A Brief visualization of the ANN implementation on the subsystems' output.

CONCLUSIONS

Pilot study showed a nonlinear process and utilizing current controls is not sufficient to improve the SDP efficiency which greatly affect the processing cost to this industry. With the SDP's current performance, the SDP is only capable of performing up to an average of 50% efficiency and in overall, and worst, the company is spending more than $1, 000, 000 annually on water disposal itself. To reduce the gap from the targeted performance; this study has identified major subsystems that each requires fine tuning, which are mainly due to mechanical factors. Upon optimization up to 90% solid content, the company is only spending less than $200, 000 for water disposal, in which is accepted by the management. Note that this optimization is implemented on an actual SDP with real optimized results. For future study to improve efficiency and constant output of the SDP, Author believes that an ANN can be implemented. This would ensure that the output cake up to 90wt% solid content is continuous repetitive. Analogue sensors must be installed and diagnostics features for sensors and system must be available to further enhance the computing system.

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