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Analysis of parabolic through collector cleaning system under adaptive scheduling policy

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ANALYSIS OF PARABOLIC TROUGH COLLECTOR CLEANING SYSTEM UNDER ADAPTIVE SCHEDULING POLICY

by

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[The supreme guide in life is wisdom and science.

–M. Kemal Ataturk, 1924]

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ANALYSIS OF PARABOLIC TROUGH COLLECTOR CLEANING SYSTEM UNDER ADAPTIVE SCHEDULING POLICY

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ABSTRACT

The purpose of this study is to investigate the effects of stochastic dust accumulations and rain events on the cleaning schedule of the parabolic trough collectors that are used to generate power at concentrated solar power (CSP) plants. The level of cleanliness is proportional to the power produced, and thus it affects the economic pay off at CSP plants. Current practice to address this dust problem, termed as conventional cleaning, is to follow a periodic cleaning schedule that entails a fixed setup cost for each cleaning event. The frequency of cleaning under such conventional (periodic schedule) policy is selected based upon a tradeoff between the set up cost and the payoff from improving the cleanliness factor. The conventional practice is to have a constant and periodic cleaning schedule over an entire season (e.g. either severe or mild combination of the dust and rain over a 180-day cleaning season, with either 8 or 4 cycles scheduled for the severe and mild seasons respectively).

This thesis draws upon evidence from recent literature to show that presence of random rain events improves the cleanliness of parabolic troughs in CSP plants. Upon analyzing such evidence, this study models rain event as a compound Poisson process that replenishes the level of cleanliness. In this

scenario, it is possible to establish an adaptive threshold policy for scheduling plant cleaning that analogous to the formulation of a (s,S) inventory management policy, subject to random replenishment of inventory. The study offers a review of related literature to establish that such formulations are not amenable to a close form solution.

The second half of the thesis describes a numerical study that has been conducted using Arena Simulation package for characterizing the adaptive cleaning policy. The parameter of interest for assessing system performance is the average payoff over the average cost of cleaning for a 180-day cleaning season. Numerical study shows that adaptive cleaning policy outperforms the conventional (periodic) cleaning policy under reasonable assumptions for dust and rain event distributions. As an extension, the simulation study also examines the use of alternative cleaning system, known as electrodynamic screening (EDS), for different rain scenarios that may be used in conjunction with either conventional or adaptive cleaning policies to improve the overall system performance.

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LIST OF ABBREVIATIONS

CF..Cleanliness Factor

CSP ....Concentrate Solar Power

DNI ....Direct Normal Irradiance

EDS .... Electrodynamic Screen

O&M ....Operations and Maintenance

PTC ....Parabolic Trough Collector

SAM..Solar Advisory Model

SNL..Sandia National Lab

INTRODUCTION

The need for energy is increasing and that need is expected to grow at an even faster rate for the foreseeable future as the indicators show that energy consumption rates increasing faster than global population growth rates [1]. Given this increased demand, in the future it is expected that traditional energy resources will be exhausted. With this awareness, today's energy demand is increasingly met by renewable energy solutions. Solar power is one of the most significant resources of the renewable energy. It offers an inexhaustible power supply opportunities from Sun, but it is unpredictable in nature. Current solar power technologies include photovoltaics, solar water heating and concentrated solar power (CSP), among which CSP is the main technological foundation of this study.

Concentrated Solar Power

Concentrated solar power plants (CSPs) are being implemented at different scales and power generation technologies, and CSP is one of the more popular techniques of solar power generation all around the world.

Concentrated solar power is a common name of renewable technology, which generates electricity by concentrating solar irradiation harvested through mirrors to a predetermined small area. The principle of generation is as follows. Concentrated solar irradiation via reflectors creates heat that is supplied to a heat-based engine. This engine uses heat to propel a generator (i.e steam turbine), which create electricity [2]. CSP plants are supported with heat storages and other additional technologies to be able to generate electricity even after sunset or during cloudy days to increase generation efficiency, stabilize power generation rates, and balance the electrical load on the grid.

Although there are different CSP technologies available, the most common use of CSP systems are either parabolic trough collector systems or solar power towers. Figure 1 shows the installed operating CSP plants by country and technology [3].

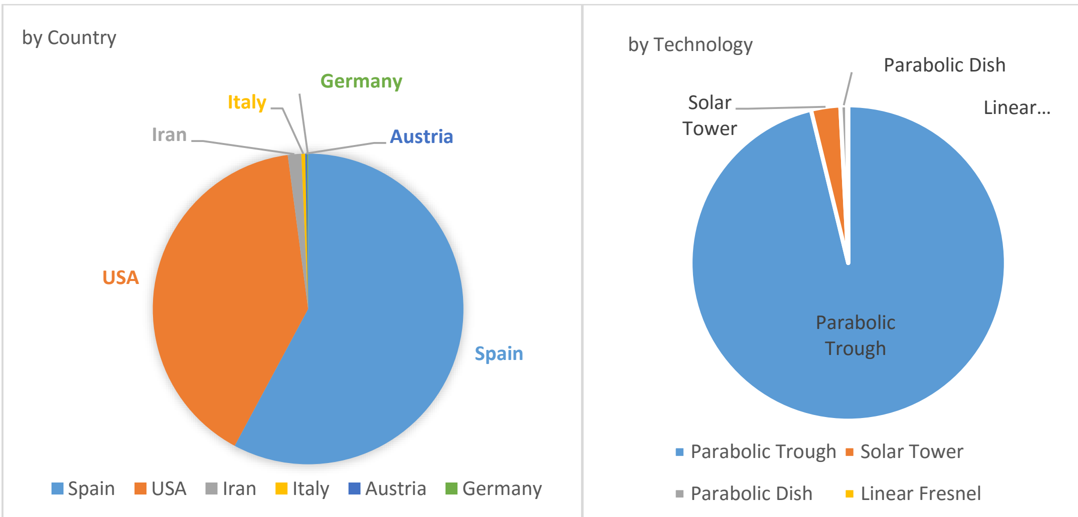


Figure 1 CSP power by country and by tech (2011)

Parabolic trough collectors (PTC) are set of reflector mirrors that reflect and concentrate solar irradiation to a small point. This concentrated sunlight heats absorber tube, which then captures the heat. Parabolic trough collectors follow the travel of the sun during the day so as to collect sunlight with most efficient angles and concentrate as much heat as possible. Electricity generation principle of the PTC systems would then follow the same principle with other CSP systems after the heat is captured [4].

CSP technology is expected to meet a significant portion of the future global power demand. One study demonstrated that CSP may cover up to 7% of global electricity demand by 2020 and even one fourth of the global demand could be met with CSP technology by 2050 [5]. For such a vast energy demand, CSP sites need to be selected carefully. Direct Normal Irradiance (DNI) is a measure used to select the most appropriate sites for CSP solar fields. The unit of DNI ,$kWh/m^2/y$, describes the sum of solar energy irradiated on the area of one square meter in a year , which is required to be at least 2000 kWh per square meter per year for a adequate CSP location. Those values mostly indicated the Sunbelt countries of the planet Earth where the North Africa, Middle East, Mediterranean, and southwest of the USA placed geographically [6]. Those places are both appropriate in terms of DNI and vast areas to establish solar collector fields.

Cleaning Problem

To keep a solar power plant economically viable over the life of plant, it is vital to minimize the cost per unit electricity generated. Indeed, O&M costs are also a significant contributor of the expenses, especially in remote locations where water is scarce and the cleaning operations are more frequent due to climatic conditions.

As a general matter of fact, each environment has its own habitat and microclimate. We will focus on CSP plants placed in arid and semi-arid regions, where two factors affect the CSP collectors: sand and thunderstorms. Dust caused by sand storm can decrease the yield up to 60% in one day, while rain can help to clean the surface of CSP mirrors. Both of these environmental factors have a significant effect on the cleaning schedule and the cost of the maintaining CSP stations. While one might assume that use of a bit of water may solve the problem, severity of the O&M cost and cleaning problem would be obvious when the CSP power blocks scale up to contain tens of thousands of reflectors, which are installed the remote and water tight locations of the planet Earth.

CSP plants need to be cleaned regularly to keep their efficiency high. Different methods exist to keep CSP reflectors clean, of which one is called the electrodynamic system (EDS), which continues to be developed. In this study, we focus on the problem of cleaning parabolic trough collectors in a CSP. Our goal is to create a more efficient cleaning policy for CSP to reduce O&M costs.

The remainder of the thesis as follows: First, we introduce the existing cleaning optimization literature, which eventually shows the potential positive effect of rain events on the cleaning schedule of the reflectors. Then we give a brief literature about the (s, S) inventory management systems under random demand, from which we get intuitions to propose an adaptive policy to cleaning problem. In the third chapter, we propose the method and model for the cleaning problem that takes intuition from random demand inventory system. Next chapter describes the numerical study and simulation of the proposed model on

Arena Simulation Package. In this chapter, we have studied the adaptive policy, traditional periodic policy and alternative cleaning solution of the EDS policy. Analyses include the parameters of the adaptive policy, compare adaptive policy and periodic policy and investigate the effect of rain arrivals on the EDS policy. At the final chapter, we discuss the results and draw a conclusion including limitations of the approach and potential future work.

LITERATURE REVIEW

The level of cleanliness of the CSP mirrors directly affects power generation, and is vital for maintaining the economic feasibility of a CSP plant. Studies began immediately after the introduction of the technologies. One of the first studies by Sandia National Lab (SNL) is dedicated to evaluate different cleaning strategies of the parabolic trough collectors. Study aimed to support the decision-making process of cleaning strategies under different conditions by creating detailed guidelines for the cleaning process of CSP plants [7]. They create nine-step guidelines to support the decision process that loaded of cleaning factors such as cleaning intervals, the cost of washing and other technical parameters. Throughout the process, researchers primarily follow the previous literature and expert views of the similar industries. The main contribution of the report is that this study is one of the first to put efforts to create a systematic cleaning guideline and indicate the practical critical points to keep solar collector fields economically viable and functionally effective [7]. Yet, the due to lack of expertise and practice on the relatively new parabolic trough collector technology, major points of the guidelines depends on assumptions. Even failure to follow guidelines does not create much cost difference, thus questions the effectiveness of the cleaning guidelines. Another SNL report, on the operation and maintenance improvement of the concentrating solar power plants, aims to reduce O&M cost plants via operational experience, real-time testing of the equipment, and recently-invented technical improvements. As a result, research successfully decreased annual O&M by 37% and water usage per MWh electricity generated by 33%. The report is important in the sense that it reviews and summarizes the real scale CSP power bank O&M project findings and proposed a reference O&M plan for the future solar field projects [8]. It can be drawn that majority of the water savings are not coming from the mirror cleaning operations thus we cannot say that study focus on the cleaning schedule. Rather, report overlooked the of the O&M cost calculations, which reduced by increasing operational effectiveness and deploying new technologies. El-Nashar investigates dust deposition patterns over the thermal collectors to evaluate the effect of seasonal dust deposition and frequency of the mirror cleaning on the performance of the solar desalination plant [9]. During his study, experimental data taken from actual plant measurements are subject to a mathematical model of performance equations such as transmittance and specific water production. As a result, it has been found that the seasonal transmittance rate varies significantly, which 0.6 transmittance rate on the very dusty collectors can reduce the plant production 40% of clean collector's capacity. The study also concludes that maximum plant production is achieved by weekly cleaning cycle among month, weekly and daily alternatives. Distillate water production is also found to vary seriously with transmittance changes between 2.7 liters per one megajoule to 1.8 liters per one megajoule for the dustiest condition, which has 0.6

transmittance rate. The experiments show that the overall power consumption of the plant is negatively correlated with the transmittance, more specifically power consumption increases while transmittance ratio decreases due to dust accumulation [9]. His study contributes the previous literature on the effect of dust accumulation and the frequency of the collector cleaning especially by emphasizing the seasonality effect. Even the subject field of the study, water desalination plant, is different from the CSP plants, the functionality of the collectors and effect of the dust accumulation on them are in the similar direction to that of other CSP plants. In addition, as this study emphasizes the local conditions, findings may vary depends on the geographic location of the plants. Further studies focus on the technical parameters of the cleaning to make CSP maintenance operation more efficient. Garcia et all have focused on the optimization of the technical parameters of the water-based cleaning method so as to find the most efficient combination of cleaning method for parabolic trough CSP [10]. Their experimental design includes three main parameters of water-based cleaning method, which are the quality, pressure, and the temperature of the pressurized water [10]. Results of the study have shown that best reflectivity results minimizing operational cost have been achieved with low washing water temperature and medium water pressures. The result of the study challenges with the previous study from late 80s and states that, water hardness, as a measure of the quality, does not necessary to be lower than 5ppm, in fact, 12 ppm water pressures gave similar results with waters have higher than 5 ppm hardness. Thus, cost of cleaning involving demineralization of the water can be avoided and the overall cleaning cost would be reduced. The study contributes the literature especially by focusing on the technical parameters and details the water based cleaning in a way that is more systematic than the previous practices. It might be worthwhile to note that this study based on observations and does not provide any mathematical or analytic approach the cost expression of the cleaning and maintenance problem of the CSP plants. One of the widely used analytical cost calculation model is developed by the SNL, called as Solar Advisor Model. Turchi, C. created a report, which aimed to update the National Renewable Energy Labs cost assessments techniques back in 1999. The study was also focused on creating a framework for SAM cost analysis section, which allows users to see the impact of individual components of the power plant on the cost [11]. The technical report studied the two different technologies, wet-cooled and dry-cooled of parabolic trough CSP plants and revealed that that dry cooling set-up requires more solar field areas and installation cost than the wet-cooling yet the overall Levelized Cost of Electricity (LCOE) for both is relatively similar. This is mainly because of the fact that dry-cooling design generates more annual power than the wet cooling set up. It was also found that the water consumption of the dry set-up is 93% lower than wet design. On the other hand, water required to clean parabolic collectors is more than the dry-cooling setup as the dry setup has lower plant efficiency [11]. The report also created the excel spreadsheet of the cost model that can be used by end user to tailor the specific CSP plant designs with respect to specific demands, sizes, and technological components. Although model offers the detailed cost calculations, it does not have the detailed O&M cost plan other than a roll-up of O&M costs. As a result the detailed analysis of the cleaning operations cannot be followed. Further studies are investigated the cleaning methods of for the CSP plants. Garcia et all measured the effectiveness of the different cleaning methods in semi-arid CSP locations [12]. They conducted the experimental test design of the cleaning methods under real outdoor conditions for two years. They showed that the detergent as an additive to water may not be as effective as expected. The number of cleaning passes is also an important factor, where 3-pass water method reaches 98.8% and 2-pass cleaning reached 97.6% cleaning rates [12]. They concluded that even the change in reflectance is significant, the additional cost of extra pass should not be neglected. Most effective cleaning method among the alternatives is determined as demineralized water with a brush, whereas the steam based method with soft tissue was found to be ineffective. The reflectance rate of the mirrors without cleaning dropped as low as 20% of it perfect clean rate yet, following periods with deluge waterfalls would be enough to recover 0.9 of max reflectance without artificial cleaning . This study shows the effectiveness of natural rainfall events as a proven cleaning method and mentions the ineffectiveness of the detergent additive under certain practices, thus minimize both the potential environmental side effects and the cleaning cost of the CSP plants. Further studies to better understand effect of soiling rate on the reflectors and cleaning mechanism of the CSP has been conducted on the Morocco [13]. Bouaddi, S. et all studied the soiling pattern of the widely used second surface silvered method and the innovative aluminum based mirrors so as to design better cleaning policies for local conditions. Their approach includes the data from local experiments and is subjected to dynamical factor analysis (DFA) and time series so as to reveal capture the trend in soiling rates among different series. As a result of the study, it has been revealed that two common factors across five time series were enough to explain changes in soiling rate at which first common trends define the general change in reflectance and the second represents the positive increments of the reflectance during the exposure period. It is al conclude that effect of the rain on the soiling rate vary based on other parameters i.e. type of mirrors, previous level of soiling. It is observed that the deluge rains were well enough the recover all the reflectance rate especially on the glass surfaces and some type of aluminum surfaces. Results on the frequency of the cleaning cycles illustrated that the monthly cleaning showed the greater effect on the cleaning of the mirrors, though grass mirrors again perform better than the aluminum ones. In general, research concludes that type innovative aluminum reflectors would tend to perform better arid dry desert condition where rare rain occasions observed whereas the glass based silvered mirrors outperform the latter under wet conditions. This study reveals the effect of rainfall on the soiling rates among different reflector technologies and specifically shows that heavy rainfall cleans the widely used mirrors very reasonably and recovers the initial clean state without artificial cleaning.

One of the most critical evidence drawn from the existed literature is that effects of the rain events has been clearly stated and improves the reflectance rate of the collectors. The aim of this thesis is to consider the natural phenomenon as a part of cleaning operations and create an adaptive model that minimizes the cost of cleaning.

With this result, the cleaning problem is modeled analogous to the inventory management policy with compound Poisson demand where the stochastic rain events supplied the Cleanliness Factor level, which is replenished up to maximum level whenever the targer cleanliness level (s) is reached. A possible implementation of such model is to apply (s, S) inventory policy where we request cleaning ordert to maximize cleanliness factor up to S when the CF position is less than or equal to target cleanliness level, *s*. Archibald et all studied the continuous review (s, S) policies with discrete compound Poisson demand to show that optimal policies exist for the single product continues review discrete compound Poisson demand systems, developed a formulation to calculate the cost of (s, S) policy [14]. The overall research investigates to decision rules of the inventory systems where erratic demands occur. They created an algorithm to find the optimum values of the cost function, and run the model with 500 samples created by using 50 probability mass function and represents the numerical findings. It is found that the cost function relatively insensitive to variations of the s and n value. Also, optimal control parameters (s^*, S^*, n) are found to be sensitive to pmf of demand transactions, especially under erratic demand. [14] Archibald et all have introduced the computationally easy to follow an algorithm to find an optimal policy for (s, S) system under continuous review. They took the pre-existed approach and enhanced it to cover special cases of the problem introduced back in 1961 by Beckmann [15]. Further studies have been conducted to find reorder point of the (s, S) policies under periodic and continuous reviews. Tijms and Groenevelt mentioned the difficulties of defining shortage cost of inventory systems while optimizing overall cost function and studied the (s, S) policy with respect to service level constraints so as to make his findings practically convenient. They extended the previous approximations to find reorder point of the periodic inventory systems to the general class of (s, S) inventory systems covering continues review case so that they can be widely used in practice. [16]. A direct approach, which simpler than the previous approximations [17] is employed to determine re-order points of the (s, S) systems. In the final analysis, it has been stated that the simple approximations for reorder points of (s, S) policies could be calculated with 2 moments normal approximations of the reorder point equations when the coefficient of the demand in lead time plus review time does not exceed 0.5. If the demand coefficient is greater than 0.5 it is suggested fit gamma distribution demand distribution rather than using normal distribution [16]. This is the first study that introduced the tractable algorithms for continuous review (s, S) policy. The algorithm is readily implementable with service level expectations yet it depends on the several assumptions including demand transactions and on hand stocks which may limit it is practical applications.

At this point, a study has been conducted to provide an algorithm to compute optimal policies for (s, S) inventory systems in a less expensive, simple and provable way **[18]** The developed algorithm has given the tighter upper and lower values for the optimal reorder and inventory level (s*, S*) than existing algorithms due to its search method with respect to some properties of the cost function. It is stated that computational efforts to find optimal (s, S) policies are less demanding and tied theoretically by 2.4 times of that of single item policy **[18]**. As it is seen from the literature, it is not possible to get close form equations of the (s, S) policies under compound Poisson demands. Thus, simulation of the model has been implemented to see the effect of the targert cleanliness point and other parameters of the model over the cleaning scheduling problem. Next section introduced the methodolgy and propose the simulation model of the cleaning problem.

METHODOLOGY AND SIMULATION MODEL

General Framework

Simulation model has been implemented using block and elements panels of the Arena Simulation package where SIMAN simulation language used to create and run the model simulation. The model, referencing the existing book model of the (s, S) inventory model [19]. Our inventory carries a single inventory item, which is the cleanliness factor (CF), and dust events demand the CF. Simulation runs for finite time period. For further information and details of the simulation model please refer to appendix. Following subsections, introduce the dust deposition, cleanliness factor and rainfall setups of the model.

Dust Deposition Setup

Dust events are modeled as Compound Poisson process, which inter arrival time of the dust events are exponentially distrıbuted with $1/\lambda_D$, dust arrival rate, and the number of dust events per arrival follows a discrete probability function. Dust deposition to the reflectors is modeled as demand event, where the dust inter arrival time is the time between two consecutive dust deposition events. Inter arrival time is exponentially distributed with constant rate during a day. Demand intensity defines the amount of dust deposition per dust events that has also a probability distribution such as uniform or normal. If the current level of the Cleanliness Factor is enough to meet dust deposition intensity then the deposition is reduced from the current cleanliness level, otherwise partial deposition is reduced with on hand Cleanliness Factor and the rest is counted as lost as the system cannot get dirtier after certain amount of dust deposited. Model does not allow backorders. The equivalent set-up for the cleaning schedule of the parabolic collectors is as follows: Mirrors continue to function with a reducing performance until the collector surfaces are totally covered with dust and thus cleanliness factor level reaches absolute predetermined minimum or zero. If this is the case, reflectors cannot collect sunlight anymore even further dust deposition continues. As the time passed during absolute dirty state cannot be reversed or stored, system lost the generation capacity during this time.

Cleanliness Factor Setup

Cleanliness Factor level after t days past from the beginning of the cycle, CF (t), is between zero to one. Therefore, in our system, level of Cleanliness Factor changes from zero to one where zero means collectors covered with dust and cannot function and one represent the perfect clean state of the collectors. Cleanliness Factor level was reviewed continuously every day at the same time. Maximum Cleanliness factor and target cleanliness level, threshold or little s, is predetermined where target level is less than current Cleanliness Factor-S-. If the Cleanliness Factor level is greater than or equal to the target level, system does not request cleaning until the next cleanliness evaluation. Cleaning requested and CF level is maximized to 1 if the Cleanliness Factor level during review is less than target cleaning level. It is assumed that cleaning delivered instantly without any delay, therefore cleaning orders simulated without lead time.

Rainfall Setup

Rain events are simulated as random free supplies with random increments to Cleanliness Factor at which no cost of any kind is incurred to model. Rain events are created with discrete compound Poisson process, where both rain arrival and rain intensity are randomly distributed. Interarrival times of the rain events are exponentially distributed with the reciprocal of the mean arrival rate of rain per day,$1/\lambda_R$. In addition number rain events, rain batch, per arrival are distributed independently, so we can simulate the rare deluge rainstorms as well as regular rain events. Rain intensity follows a random distribution, which is independent from the rain events distribution and determines the effect of the rain events on the CF. Rain effects update the Cleanliness Factor level prior to rain arrival in a delayed manner, to simulate natural duration of the rain, after which cleaning effect becomes effective. Rain delay could be either deterministic or stochastic variable. To illustrate, if the rain lead-time is uniformly distributed between 0.1 and 0.2 hour a day, duration of the rain takes 2.4 hours to 4.8 hours to complete and effect of the rain is then assigned to the current level of Cleanliness Factor.

Cost Structure of the Model

In our model, any dust demand cannot meet from on hand Cleanliness Factor is counted as lost, which has no cost incurred the model. Every time cleaning requested has a fixed cost of operation, which sums up to the total cleaning ordering cost. Holding cost is on the other hand is proportional the power generated and calculated regarding to the complement of Cleanliness Factor level which explained in details in the following subsections.

Ordering Cost

Unit Order cost, C_o is placed when the new cleaning request has been made with a fix rate regardless of the amount of the contribution of the cleaning to Cleanliness Factor Level, thus no additional incremental cost per unit Cleanliness Factor applies. If the Cleanliness Factor level is above the target level, s, with random rain supplies, then no order is requested so there is no ordering cost. The decision is illustrated with the indicator function. At the end of simulation, total of ordering cost is divided by the length of simulation time and average ordering cost is calculated. Equation below shows the total and average ordering costs

$$Total\ Ordering\ Cost = \sum_{0}^{T} C_o * 1\{CF(t) < s\}\,(K)$$

$$Average\ Ordering\ Cost = \frac{\sum_{0}^{T} C_o * 1\{CF(t) < s\}\,(K)}{T}$$

Where T is the length of simulation, t is the corresponding day of the, 1 is indicator function, s is the ordering point (0<s<1), K is the fixed cost of ordering new cleaning simulation and CF(t) is the Cleanliness Factor Level of the t^{th} day.

Holding Cost

For the regular inventory system, holding cost calculates the inventory (CF) we carry during the operations, so whenever the CF is greater than zero, holding cost of certain dollar amount per unit inventory item per day applies as cost. However, as higher the CF is higher the power generated, profit comes through the Cleanliness Factor we have. Whenever the Cleanliness Factor go below the maximum level we will lose profit by keeping our Cleanliness Factor level is low. Therefore, the complementary of the conventional holding cost calculation would be what we define as the holding cost of the cleaning operations. Overall holding cost is the sum of complementary daily Cleanliness Factor level, max Cleanliness Factor level minus current Cleanliness Factor level, trough out the simulation time multiplied by unit holding cost. Average holding cost is calculated by dividing total Cleanliness Factor cost into length of simulation.

$$Total\ Holding\ Cost = \int_0^T C_h * \max(1 - I(t), 0)dt$$

$$Average\ Holding\ Cost = \frac{\int_0^T C_h * \max(1 - I(t), 0)\, dt}{T}$$

Where T is the length of simulation, t is the corresponding day of the simulation and I(t) is the Cleanliness Factor Level of the t^{th} day.

Data Structure of the Model

Blocks and Elements panels of the Arena simulation are used explicitly to describe events, expressions, statistical controls, and to run the overall model.

Variables Element

Variables used to describe model components that revels the information about the system [20]. All of the variables are global means that apply to all entities of the model, which are given below as table. Cleanliness Factor Level is the current level of CF at any time t and with initial CF set to 1. Cleanliness Factor level (CF) is reviewed after the rain events, which is the position of Cleanliness Factor level after the effect of rain is completed. Cleanliness Level also updates after each dust deposition, which deducts Cleanliness Factor level upon arrival of dust events. Order up to level, Big S, variable is the maximum level of CF when the system request a new cleaning, which is one at the perfect clean state of the collectors. Target cleanliness level, Little s, is selected by system operators and release the new cleaning when Cleanliness Factor reaches the target level, which is the minimum desired CF of the reflectors. Days to run variable defines the time horizon of the simulation. Unit holding cost is used to accounts relative benefits comes through cleanliness of the reflectors. This is the counter of the traditional holding cost as the normal inventory incurs the items on hand. In our case, we would like to keep cleanliness factor as high as possible to make profit via power generation. Thus, holding cost is the cost of not cleaning reflectors, and applies daily. Unit setup, ordering, cost is the cost single clearing operations, which incurs a fix cost per cleaning. Total ordering cost variable is the sum of holding and fixed set up cost variables, which together defines the cost of the system at the end of simulation. Table 1 summarizes the variables used in the simulation model.

Variables Element	Definitions	During Simulation	Initial
Cleanliness Factor Level = CF(t)	Current level of CF, (reviewed after demand and rain occurs)	Changes	1
Order up to Level, Big S = S	Order up to Level	Fix	1
Target Cleanliness Level ,Little s,=s	Where to order	Fix	Up to user
Days to run	Length of Simulation	Fix	Up to user
Unit Holding Cost	Cost of carrying dust which reduce CF	Fix	Up to user
Unit Setup (Order) Cost	Cost of New Cleaning	Fix	Up to user
Total Ordering Cost	Holding*Cleanliness Factor+ Setup*Total Cleanings+	Accumulates	0

Table 1 Variables Element of the Simulation

Expressions Element

Expressions are used to calculate distributions and values of characteristics of the entities [21]. Dust interval expression defines the time between consecutive dust arrivals, which are exponentially distributed with the inverse of the arrival rate of the dust event. Review interval is the evaluation frequency of the Cleanliness Factor model at the default it is set to one so as to keep policy adaptive to daily changes of the Cleanliness Factor level during simulation. Rain interval expression defines the time between two consecutive rain events, which is a Compound Poisson process with mean rate of $\lambda_{2.}$ Demand intensity expression is a random variable, which defines the magnitude of the dust arrivals. Rain batch is an expression that defines the number of rain events per arrival, which is the instant number of events, happening at the same time. If the event per arrival is more than one, the effect of the event on the cleaning factor is simply multiplied, so system successfully simulate rare events like rain storms, besides the expected rain events. At the same way, dust batch is used to simulate rare and more severe dust storm events by increasing number of dust deposition events occur instantaneously. Table 2 summarizes the expressions element of the simulation.

Expressions Elements	**Definition**	**Distribution**
Dust Interval	Time between two consecutive dust arrival	EXPO($1/\lambda_D$)
Review Interval	Cleanliness Factor review entity	Beginning of each day
Rain Interval	Time between two consecutive rain events	EXPO($1/\lambda_R$)
Dust (Demand) Intensity	Effect of the dust over Cleanliness Factor	NORM(μ_D, σ_D)
Rain Intensity	Effect of the rain over CF Cleanliness Factor	NORM(μ_R, σ_R)
Rain Batch	Number of rain events occur per arrival	DISC(P_i,V_i)
Dust Batch	Number of rain events occur per arrival	DISC(P_i,V_i)

Table 2 Expressions Element of the Simulation

Attributes Element

Attributes used to define objects of the model and characteristics of the entities. Attributes could be defined as many as needed [21]. In our model, order quantity attribute defines to amount of CF delivered to maximize Cleanliness Factor level to one when the cleaning is requested. Table 3 shows the attribute element of the simulation.

Attributes Elements	Definition	Variable
Order Quantity	Amount request to maximize CF whenever the cleaning requested	Big S- Cleanliness Factor Level

Table 3 Attributes Element of the Simulation

Entity Elements

The entity elements define entity types that may be assigned to entities in the model. Entities are the actual players of the system that moves, arrives and leave the system. Entities could affect or could be affected by other entities defined in the system [20]. In this simulation we have three different entities for each subcomponent of the model. Dust event entity defines the dust deposition events, which reduce the CF, so the power generation capacity decreased. Rain event entity defines the rain arrival, which is assumed to increase the reflectance rate of the collectors, thus increase the cleanliness factor (CF). Cleanliness Factor Evaluator is the daily evaluator entity to check the CF during simulation. Table 4 represents the entity elements of the simulation.

Entity Elements	Definition
Dust Events	Dust events that demand CF to generate power
Rain Events	Rain events enter to system which assumed to increase CF level
Cleanliness Factor Evaluator	Act as operator to check system CF level

Table 4 Entities Element of the Simulation

Replicate Element

The replicate element specifies the number of simulation replications, the beginning time of the first replication, the maximum length or terminating condition for each replication, the type of initialization to be performed between replications, and the time period after the beginning of the run at which statistics are to be cleared. Days to Run element is used to control length of simulation. Time unit of the all expression and entities is a 24-hour cycle. Table 5 shows the replicate element of the simulation below.

Replicate Element	Definition	Length	Base time Unit
Days to Run	Details of the simulation duration	Days to Run	Days (24 Hour)

Table 5 Replicate Element of the Simulation

Project Element

The project element is used to label the Summary report, which is a statistical summary of the simulation responses for each replication [21]. Project elements generated the end of each simulation replication. Cleaning operations is the given name of the simulation, which will name the reports at the end of simulation as well.

Counter Elements

The counter element specifies parameters for counters that may be used to keep integer count statistics on events occurring in the model [21]. Cleaning Order counter the number of cleaning orders requested during simulation. Table 6 describes the project elements of the simulation.

Project Elements	Definition
Cleaning Order Counter	Counts how many times the cleaning requested

Table 6 Counters Element of the Simulation

Output Elements

The outputs element defines using SIMAN expression language, which are to be reported in the SIMAN Summary Report and optionally recorded in output files or reports at the end of each replication of a simulation [21]. Average Ordering cost is defined as the expected cost of ordering cost per unit time, which could be find by dividing total ordering cost to duration of the simulation. Total ordering cost is the sum of the ordering cost and holding cost, which are introduced before. OVALUE and DAVG are the SIMAN expressions that return the most recent value of the ordering cost and the time persistent average of the holding cost respectively. Table 7 displays the outputs elements used in the simulation.

Output Elements	Definition	
Average Ordering Cost	Expected cost of cleaning per day	Total Ordering Cost/Days to Run
Total Ordering Cost	OVALUE returns the most recent value ordering cost and DAVG returns the time persistent average of holding and shortage costs	OVALUE(AVG Ordering Cost)+DAVG(Holding Cost)

Table 7 Outputs Element of the Simulation

Logical Flow of the Cleanliness Factor Simulation

Dust Management

System starts with the clean phase, at which the initial Cleanliness Factor is set to one, perfect cleanliness. The demand arrivals are modeled as discrete compound process where the arrivals fit the Poisson process with arrival rate and batch size of the arrivals distributed with discrete probability function introduces as expression elements. Effects of the dust depositions are modeled with the dust intensities that model the intensity with normal distribution's first two moments. Inter-demand time describes frequency of the demand events and exponentially distributed with $1/\lambda_D$. If the Cleanliness Factor level prior to dust demand greater than or equals the cleaning reorder threshold, little s, then the demand is reduced from the current Cleanliness Factor level. If the dust intensity is bigger than the current Cleanliness Factor level then the partial demand is meet and the rest is lost, as the system does not allow backorders. Figure 2 illustrates the flow of demand management module of the model.

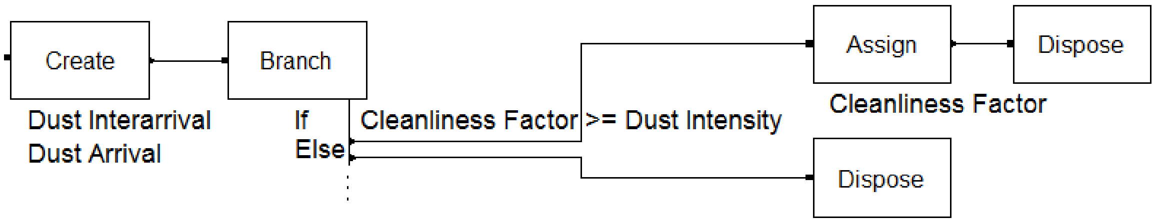


Figure 2 Dust Events Simulation Flow

Rain Management

Rain events are created with the given rain inter-arrival expression and rain duration is simulated with Rain Effect Delay expression whenever it occurs. Rain arrivals are a discrete compound Poisson process where the time between two consecutive rain arrivals is exponentially distributed and the batch size of the rain arrivals has the cumulative discrete distribution. Rain Intensity is also random variable describing the eventual cleanliness effect of the rain upon arrival. Cleaning effect of the rain is added to Cleanliness Factor level, after rain delay to simulate the duration of rainfalls. If the overall Cleanliness Factor level become greater than the S=1, overall Cleanliness Factor Level is assigned 1 as the regardless of the rain and intensity reflectors can't go above the perfect clean state. Otherwise, rain added Cleanliness factor is assigned as overall Cleanliness Factor level. Figure 3 displays the rain events arrival and management simulation flow of the model.

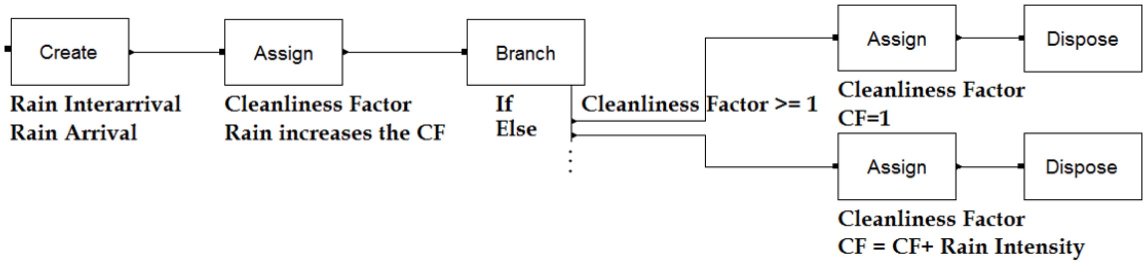


Figure 3 **Rain Events Simulation Flow**

Cleanliness Evaluation

Cleanliness Factor Evaluator block starts checking Cleanliness Factor level at the beginning of the first day with defined Evaluation interval, which is set to 1 to ensure continues review policy. Brach block determines whether to request a cleaning or not by checking the current level of the Cleanliness Factor after the dust demands and rain supplies. If the Cleanliness Factor level is less than the threshold CF level, little s, than cleaning is requested to maximize CF up to S =1 again. If the Cleanliness Factor Level is greater than the little s then, branch does not assign any order. Figure 4 express the logical flow of the continuous Cleanliness Factor evaluation diagram of the model.

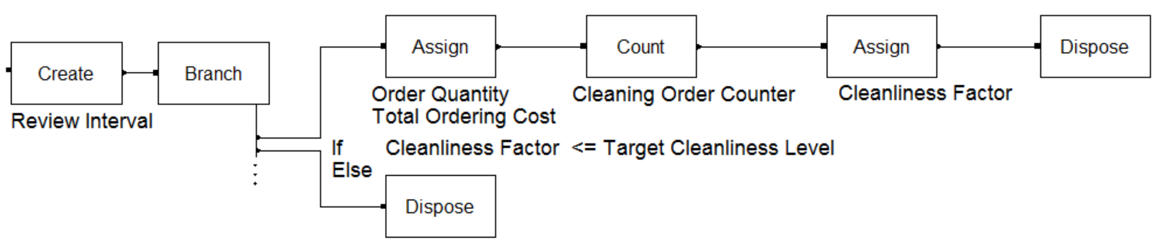


Figure 4 **Continuous Cleanliness Factor Evaluation Flow**

NUMERICAL ANALYSIS & RESULTS

Cleanliness factor term has been taken from the literature that defines Cleanliness factor as ratio of the reflectance of soiled mirror to those of clean mirrors [13]. Dust arrivals are modeled as discrete events where the intuition comes from the calculation of the daily average degradation of the soling rates because of continues dust deposition, which decrease the cleanliness factor of the reflectors proportionally to the maximum cleanliness factor rather than gram per unit square unit. Rain arrivals are also modeled as discrete events with respect to Compound Poisson process. During simulation, rain and dust events are assumed to arrive 24-hour cycle and the new cleanliness factor evaluator enters the system every day immediately after midnight. Batch size of the rain and dust event per arrival follows a discrete distribution. Dust and rain arrivals assumed to be show their effects on the current cleanliness factor upon arrival without any delay. As such new cleaning orders assumed to be delivered without any lead-time and maximize the cleanliness level immediately. System does not have any order to process either the effect of dust deposition or rain arrival. Cleanliness factor updates in timely order of the arrivals, meaning that first entity enter the simulation processed and assigned first.

Adaptive Policy Model

The adaptive policy model is numerically studied to see the effect of various parameters on the total cleaning ordering cost. For base scenario of the adaptive model, target cleanliness value that trigger new cleaning cycle has been tested for 10 different levels of Cleanliness Factor which are 0.6, 0.65, 0.7, 0.75, 0.8, 0.85,0.88, 0.9, 0.92 and 0.95 respectively. Rain events arrived with Compound Poisson process with arrival rate of 0.4/day and number of rain events per arrival is distributed with discrete cumulative probabilities where there is 0.7 chance of single rain event and 0.3 change of double rain event possible in an any instant arrival ,DISC(0.7,1;1,2). Effect of the rain on the Cleanliness factor per rain event is normally distributed with the mean of 0.15 and standard deviation of 0.1 proportional the maximum Cleanliness Factor. Dust deposition are also fit to discrete compound Poisson process where the arrival rate of dust events is 0.4/day and the number of dust arrivals are follow the same discrete probability distribution with the rain events. Demand of the each dust event is normally distributed with the 0.04/CF mean and 0.01/CF standard deviation per day. Demand and supply size of the events are defined in terms of Cleanliness Factor. To illustrate, dust size of 0.04/CF on average, reducing the max Cleanliness factor 4% from 1 to 0.96. Set up cost of ordering new cleaning is fixed $2 per cleaning and unit-holding cost of any degradation of the Cleanliness Factor is $1 per day. With this setup, 96 different dust events reduce the CF, where as the 10 rainfalls support the CF level and total number of 10 cleaning operations are performed which cost 0.225 per day of operation. It is important the note that as the table values show the average of 30 replications, some of the events are shown with decimals but for convenience any decimal be rounded to next integer. For the ease of computation, replications of the simulation have been hold as 30 and 100 for different analysis. At the appendix section, reader can be found the test of the robustness with 1000 reps, which shows that no major difference existed between lower rep simulation and the 1000 reps test results. Table 8 below shows the parameters selected for the Base Adaptive Policy Model.

Control Parameters								
Reps	Little s	μ Rain Size	σ Rain Size	Lambda Dust Rate	μ Dust Size	σ Dust Size	Setup Cost	Holding Cost
30	Vary	0.15	0.1	0.4	0.04	0.01	$2	$1

Responses					
Total Cleaning Orders	Total Dust Events	Total Rain Events	Average Holding Cost	Average Order Cost	Average Total Cost
11	96	10	0.107	0.118	$0.225

Table 8 Parameters of the Base Adaptive Policy Model

Variations of the Cleanliness Factor during simulation have been represented at Figure 5. For this particular graph, base model has been run for 0.75 target cleanliness level. Cleaning epochs could easily be observed by following sharp escalations of the Cleanliness factor at which the system evaluator decides to request new cleaning. This is the first replication of the 180-day simulation. Actual results have been obtained by averaging thirty replications of the model.

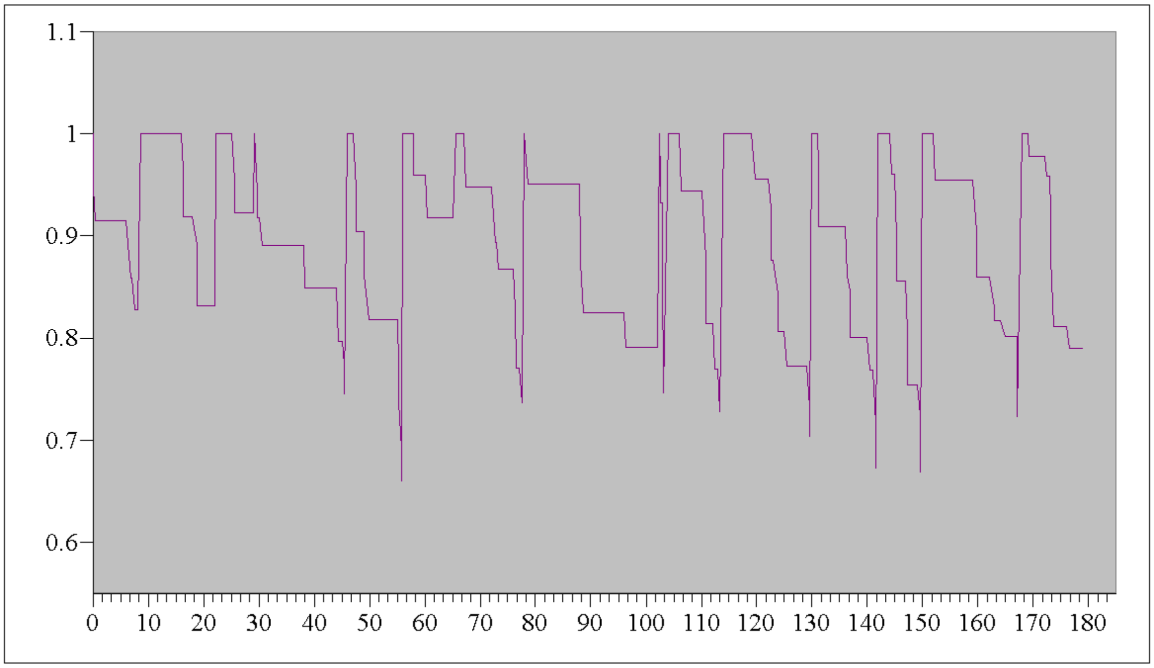


Figure 5 Cleanliness Factor Change of the Base Adaptive Policy

Figure 6 shows the average cleaning cost of the model during 180-day period. Graphs represent the average total cleaning cost values of the operations with respect to different threshold values of the cleaning decision. As it is seen, the cost minimized when the 0.75 of the maximum cleaning factor is selected as a threshold of the new cleaning cycle.

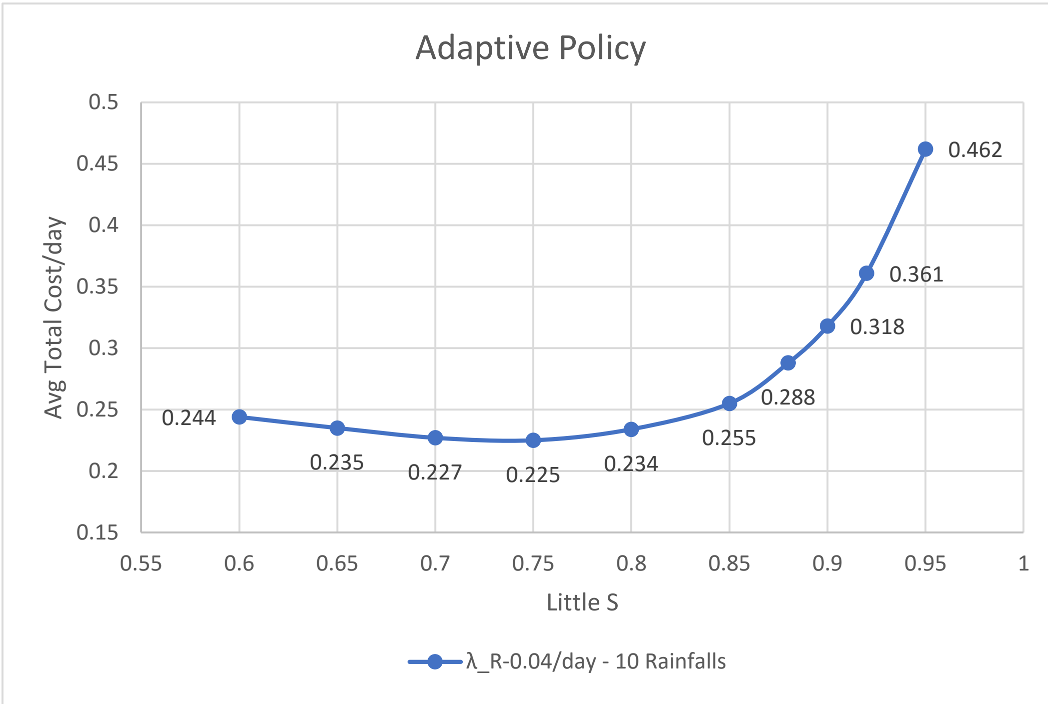


Figure 6 Average Total Cost of the Base Adaptive Policy Model

Effect of Rain Arrival Rate

The effect of rain events has been investigated in this section where we tested the adaptive model with different arrival rates of the rain. Base Model is subjected to the three different arrival rate and no rain case has been considered as base model for comparison. To name, rain rates are selected as follows: 0.02, 0.04 and 0.08 arrival rate per day with the previous batch size distribution of the base case, DISC(0.7,1,1,2). Then results of analysis on the overall cleaning cost with varying threshold values have been shown in the Figure 7 below. 0.02 arrival rate corresponds to the 5 rainfall, 0.04/day corresponds to 10 and 0.08 arrival rate per day corresponds to the 19 rain events through 180 day simulation. At first, it is clear to the positive effect of rains on the total average cost. Independent from the target cleanliness values of the system, average cost of cleaning decrease gradually while the rain arrivals increase. Base model without rain reaches optimal minimum cost of cleaning with 0.7 order point. Model with 0.02 arrival rate has dual optimum with 0.7 and 0.75, and 0.04 rate reached optimum at the 0.75 as well. It is observed that the increased arrivals of the rain events first rise target Cleanliness level thus increase the potential power generation of the power plant while keeps the maintenance cost relatively constant and then decrease back the starting point if the rains frequencies are continue to increase. At 0.75, rainfalls drove down the cost from 0.258 to 0.197, which is more than 23% cost savings. On the higher side of the cleaning threshold, system cleaning tends to merge yet again the effect of the rain arrivals still valid. Total cleaning cost of the system reaches 0.471 without rain, which drops to 0.452 with the 0.08 arrival rate of the rain. This still accounts for 4% savings on the daily cost of cleaning.

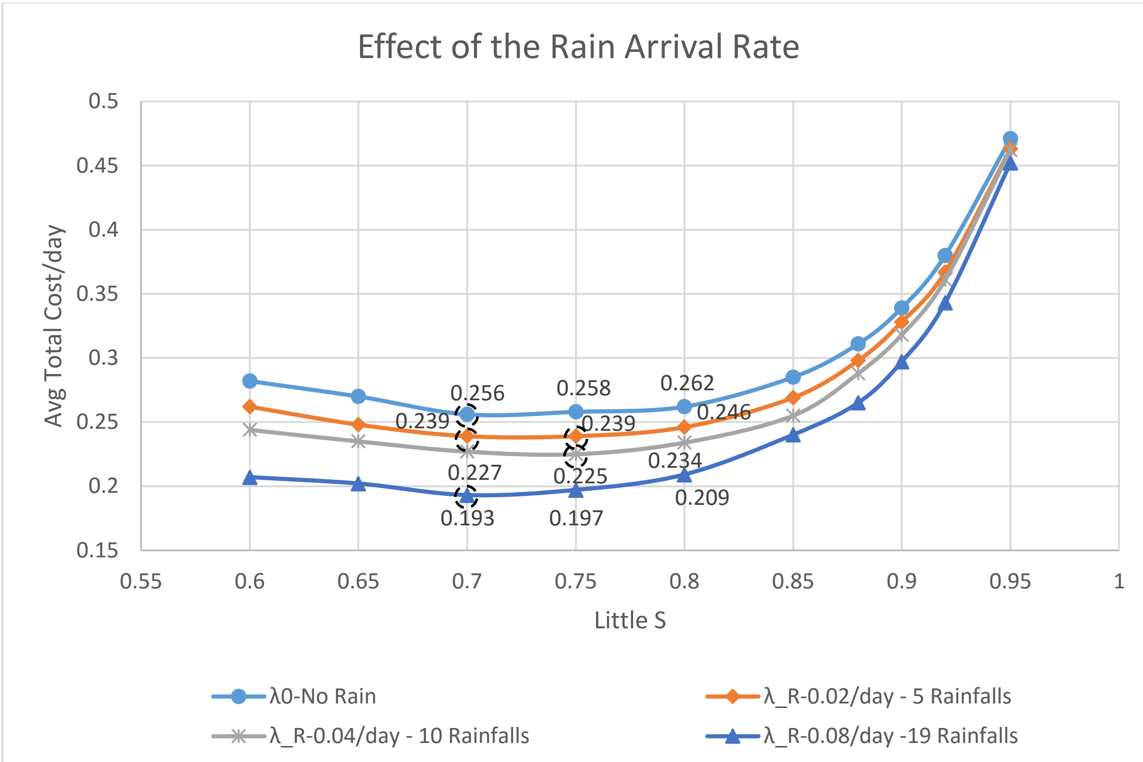


Figure 7 Effect of the Rain Arrival Rate

Effect of Dust Arrival Rate

At this analysis, effect of the dust arrival is studied, in the similar way it has been done with the rain arrivals. Other parameters, introduced as base adaptive model, have remained unchanged, except the daily dust arrival rates. Three different dust deposition rates have been subjected to cost analysis, which are 0.1, 0.4 and 0.7 per day respectively. Different rate of dust arrivals may represent the seasonality of the CSP plant locations where the dust average deposition frequencies may vary greatly. The first and the least rate of dust arrival represent the low dust season, 0.4/day represents the regular season and the last is the most dust heavy season. Figure 8 illustrates the variations of the average cleaning cost with respected to different cleaning target cleanliness level. The effect of dust deposition frequencies clearly illustrated at Figure 8 where the cost difference is more than six times when we compare the 0.95 threshold value of 0.1 and 0.7 arrival rates. The average cleaning cost of 0.725 is calculated at 0.95 cleaning point at the heavy season where the cost vary in between of the 0.32 for the 0.6 and 0.725 for 0.95 cleaning limits. At the so called 'regular season' with the 0.4/day arrival rate cost of cleaning range from $0.244 at 0.6/CF to $0.462 at 0.95/CF cleaning threshold. The least deviation of the cost has been observed at the low dust season with only 0.1/day arrival rate where the cost fluctuated in between $0.089 at 0.85/CF to $0.137 at 0.95/CF. Furthermore, in the light of information provided by simulation we can see that the cost of the overall cleaning is optimized for different arrival rates. For the low dust season, lowest cost of cleaning, $0.089/day has been observed at the 0.85/CF target level. For the regular season with 0.4 arrival rate cost function reach its optimum, $0.225/day at 0.75 whereas the high season we cannot observe an optimality as the cost continues to increase with the higher cleaning order thresholds as expected. This means that if the system experience very high dust deposition, policy can no longer find an optimum target level that both satisfy the cleaning threshold and minimizes the cost of cleaning.

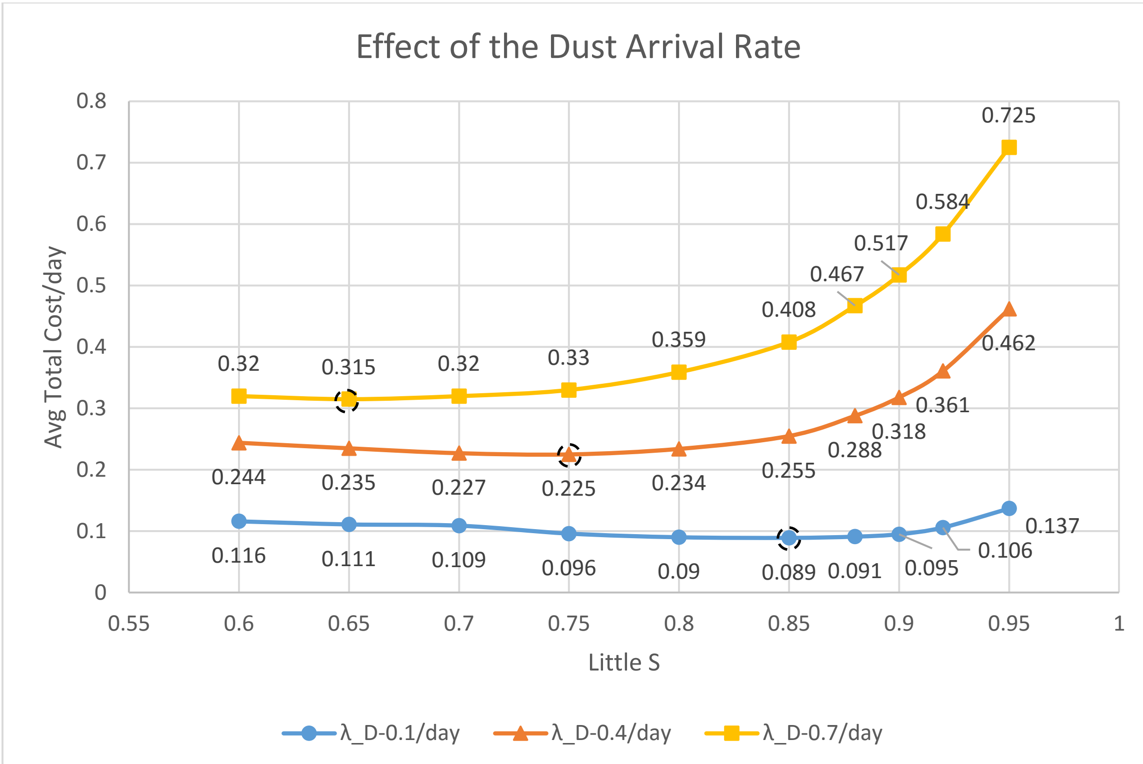


Figure 8 Effect of the Dust Arrival Rate

Effect of the Mean Dust Intensity over the Total Cost

Dust is one of the most important parameters that directly affect the cleanliness factor. Dust intensity is the actual impact of the dust deposition over the surface of the reflectors. Dust intensity, is normally distributed with mean 0.04/CF, and 0.01/CF standard deviation for the base policy. To see the impact of the dust intensity, we have considered the three different mean deposition level of the dust, which are 0.01, 0.02 and 0.04 mean dust intensity proportional the maximum Cleanliness Factor per day respectively. To illustrate, if the dust intensity of the any dust event is 0.01 it will reduce the current Cleanliness factor of the reflector by 1%. Figure 9 below shows the effect of the mean dust intensity on the average total cost of cleaning with respect to different threshold values. First, 0.01 mean intensity of the cleaning cost spans from \$0.152 at 0.95/CF to \$0.1 at 0.6/CF and reaches its minimum value of \$0.087/day at 0.85 cleaning threshold. Second, 0.02 mean dust intensity increases the cost of cleaning, which run from \$0.179 at 0.6 to its maximum of \$0.284 at 0.95 and reaches optimum values of \$0.148/day at 0.8/CF target cleaning point. When the dust intensity rises to 0.04, cost trend line jumps to \$0.462–\$0.244 range for the 0.95 and 0.6 target cleaning levels respectively, and achieved the optimal minimum cost, \$0.225 at 0.75 target cleanliness level. The effect of the rising dust intensity is clearly observed and cost function finds optimal minimum for all three values at 0.85, 0.8 and 0.75 respectively.

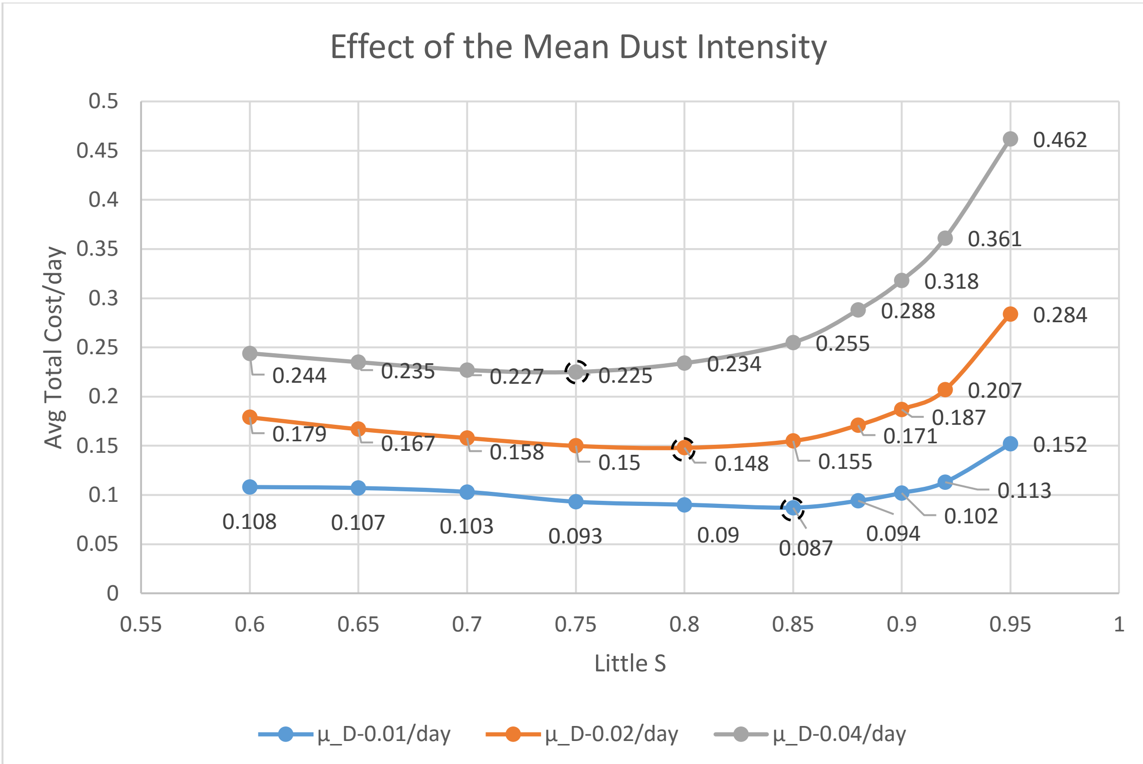


Figure 9 Effect of the Mean Dust Size

Effect of the Mean Rain Intensity

Similar to the dust intensity, rain intensity is the impact of rain events on the overall Cleanliness Factor. In this part, the marginal impact of the rain size without changing the arrival rate of the rain has been observed. Three different value of the average rain intensity have been studied, which are 0.15; 0.3; 0.6/CF per rainfall respectively. The rate of rain arrivals kept at the 0.04 per day (10 Rainfalls total) and the rest of the parameters are same with adaptive base policy model. Figure 10 illustrates the outcome of the rain intensity analysis, where mean rain intensity of 0.15/CF ranges from \$0.244 to \$0.462 for 0.6 to 0.95 of the cleaning reorders. Mean intensity of 0.30/CF per arrival corresponds to slightly reduced cost function, which ranges from \$0.226 to \$0.456 while target levels rises from 0.6 to 0.95 proportional the CF. The last and the most intense rain intensity modeled the cleaning cost function almost the same way with the 0.3 rain intensity. At the most dense rain case, cost of cleaning oscillates from \$0.22 to \$0.456 at 0.95/CF and reaches dual optimum cost of \$0.212 at 0.65 and 0.7 of the cleaning threshold values. 0.3/CF rain intensity reaches minimum cost of the cleaning \$0.213 at 0.7. Finally, the least dense option minimizes the cost function as \$0.225 with 0.75 threshold value point.

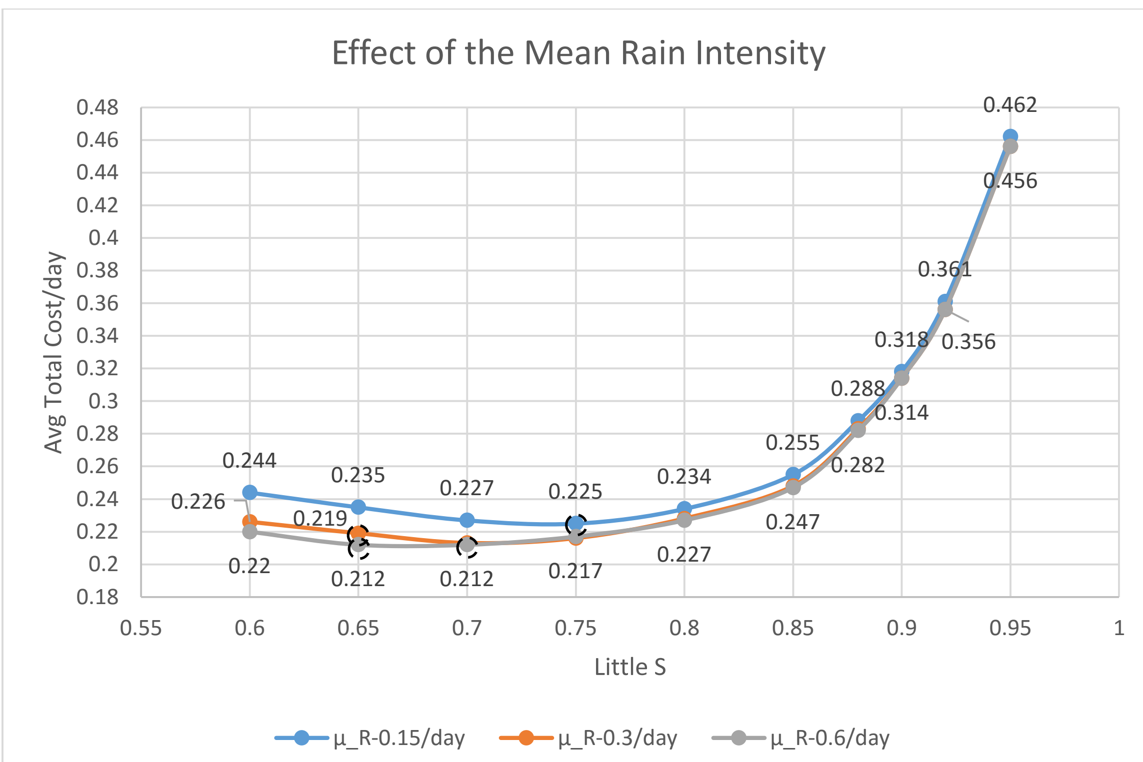


Figure 10 Effect of the Mean Rain Size

Effect of the Setup-Holding Cost Ratio

The cost function of the policy consists of two components: holding cost and setup cost. Holding cost is the sum of daily holding cost of the Cleanliness Factor, which is the cleanliness factor in our model. It is incurred daily whenever the level of the Cleanliness Factor is less than one. On the other hand, set up cost is the fixed cost of ordering that happens when Cleanliness Factor fall below the threshold reorder value of s. Holding cost, is in some sense, is the value of the power generated through the Cleaning Factor thus and important indicator of the generation. When it is low, meaning that Cleaning Factor kept high so the power generation is increased and CSP continue to be profitable. For those reasons, relative ratio of the setup cost and holding cost is important parameters to see the behavior of the cost function under different threshold values and to find optimal reorder value. Setup holding cost ratio is the ratio of cost of new cleaning to relative benefit (in terms of average power delivered) of cleanliness of the panel. If the ratio increase than the cost of cleaning becomes more significant than the cleanliness level of the reflectors. In contrast, if the holding cost increase than the higher cleanliness level becomes vital than the cost of maintaining that cleanliness trough new cleaning cycles. During the analysis unit holding cost is fixed at $1 per day and the corresponding set up cost is changed from $0.5 to $2 per cleaning with 0.5 increments while keeping unit holding cost at flat $1 per day. Figure 11 demonstrates the cost functions of the average cleaning cost with different setup-holding cost ratios. First, setup-holding ratio is selected as 0.5, which fluctuates the cost function between \$0.13/day at 0.95/CF to \$0.193/day at 0.6/CF cleaning reorder point, and optimum \$0.109/day cleaning cost is reached at 0.88/CF reorder point. Second, fixed set up cost and unit holding cost has been considered equal at \$1, which limits the cost function in between \$0.21/day at 0.6/CF and \$0.239/day at 0.95/CF, and reach optimum at 0.8/CF reorder point with the cost of \$0.157/day on average. Then, 1.5 ratio of the cost pair, function reach double optimized points at 0.75/CF and 0.8/CF with the cost of \$0.194/day. For the base set up holding cost ratio, function reach flat minimum cost rate of \$0.223/day at the 0.75/CF and 0.7/CF cleaning reorder points. For the quadruple setup cost of the unit holding cost case, cost of cleaning tends to increase exponentially while the reorder point increases. Adaptive policy cannot minimizes the total cost of cleaning with respect to different target cleanliness levels means that relative benefit can no longer payoff the marginal cost of new cleanings.

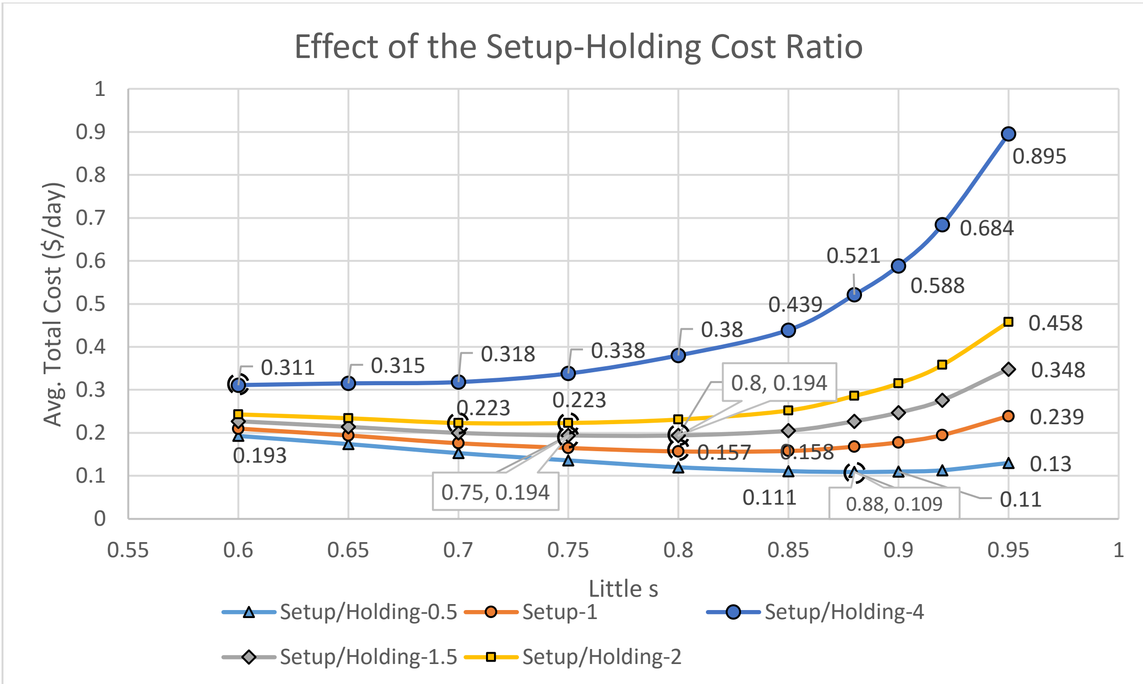


Figure 11 Effect of the Setup-Holding Cost Ratio

Traditional Periodic Policy Fixed Cycle

Traditional Periodic Policy is the widely used policy to maintain cleanliness of parabolic trough reflectors at concentrated solar power fields. In this policy, reflector surfaces are cleaned with fixed periods, which are predetermined and do not considered the dynamic whether conditions. Instead, they change the fixed cleaning cycle length seasonally such as shorten the interval at dusty summer reasons and lengthen at the rainy winter season. In this section, we will simulate the traditional cleaning policy and then compare the results with the adaptive policy. In contrast, the adaptive policy, traditional policies are independent from the target cleanliness points once the estimated cycle length has been determined. Periodic policies neglect the weather conditions once they are established thus cannot adapt the change of the weather conditions including rain and dust arrivals. First constant demand rate periodic cycle policy, case 1, is introduced and then periodic policy is updated with Poisson dust arrivals, case 2. Then results of the both cases are compared with that of adaptive policy. At the case one, dusts arrive every day with constant deposition rate of 0.04/day. Table 9 below shows the parameters and responses of the base periodic cycle policy.

Control Parameters-Constant Demand						
Reps	Cycle Length	Dust Arrival	μ Dust Size	σ Dust Size	Setup Cost	Holding Cost
30	15	1	0.04	0	$2	$1

Responses					
Total Cleaning Orders	Total Dust Events	Total Rain Events	Average Holding Cost	Average Order Cost	Average Total Cost
11	180	10	$0.283	$0.122	$0.406

Table 9 Parameters of the Periodic Cycle Policy with Constant Demand

Figure 12 shows the Cleanliness Factor Level of the periodic policy after it has run to completion.

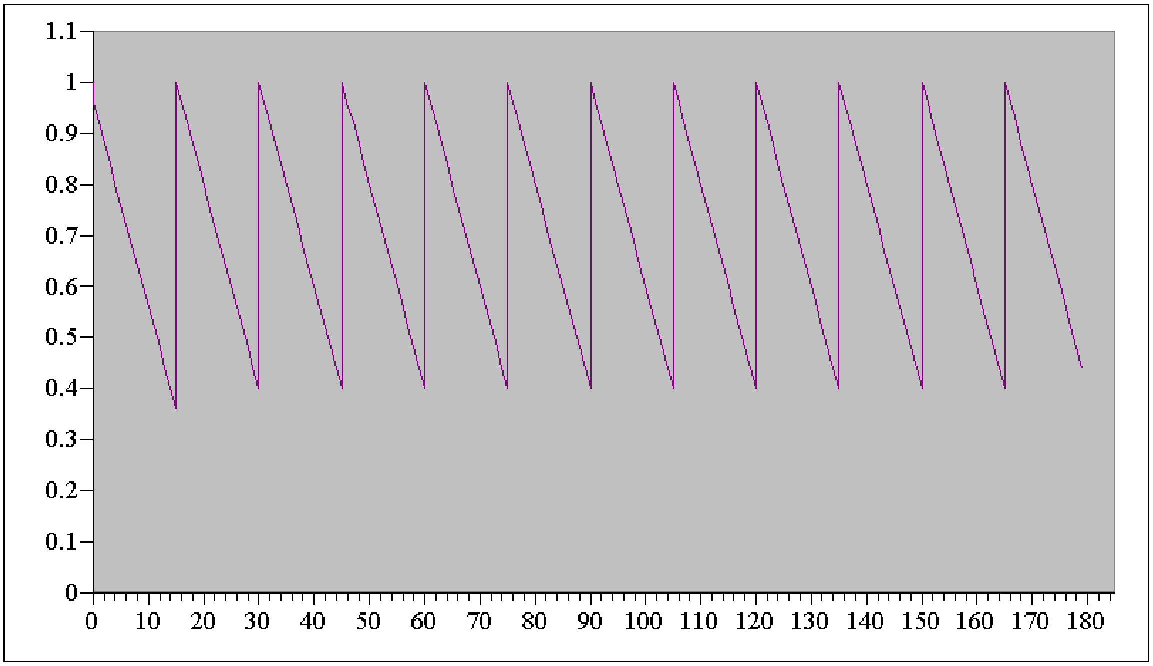


Figure 12 Periodic Cycle-Constant Intensity Everyday Dust

At case 2 of the periodic policy, Poisson demand dust arrival follows the 0.4/day dust arrival rate and constant dust deposition rate of 0.04/day. This case has the same dust process of the adaptive policy. Table 10 below shows the base fixed cycle policy with Poisson demand arrivals like the adaptive base model policy.

<table>
<tr><td colspan="7">Control Parameters-Poisson Demand</td></tr>
<tr><td>Reps</td><td>Cycle Length</td><td>λ=0.4 Dust Arrival</td><td>μ Dust Size</td><td>σ Dust Size</td><td>Setup Cost</td><td>Holding Cost</td></tr>
<tr><td>30</td><td>15</td><td>Expo(1/0.4)</td><td>0.04</td><td>0.015</td><td>$2</td><td>$1</td></tr>
<tr><td colspan="7">Responses</td></tr>
<tr><td colspan="2">Total Cleaning Orders</td><td>Total Dust Events</td><td>Average Holding Cost</td><td colspan="2">Average Order Cost</td><td>Average Total Cost</td></tr>
<tr><td colspan="2">11</td><td>95</td><td>0.158</td><td colspan="2">$0.122</td><td>0.28</td></tr>
</table>

Table 10 Parameters of the Periodic Cycle Policy with Poisson Demand

Figure 13 illustrates the instant Cleanliness Factor simulation of the periodic policy, case 2, with Poisson dust process.

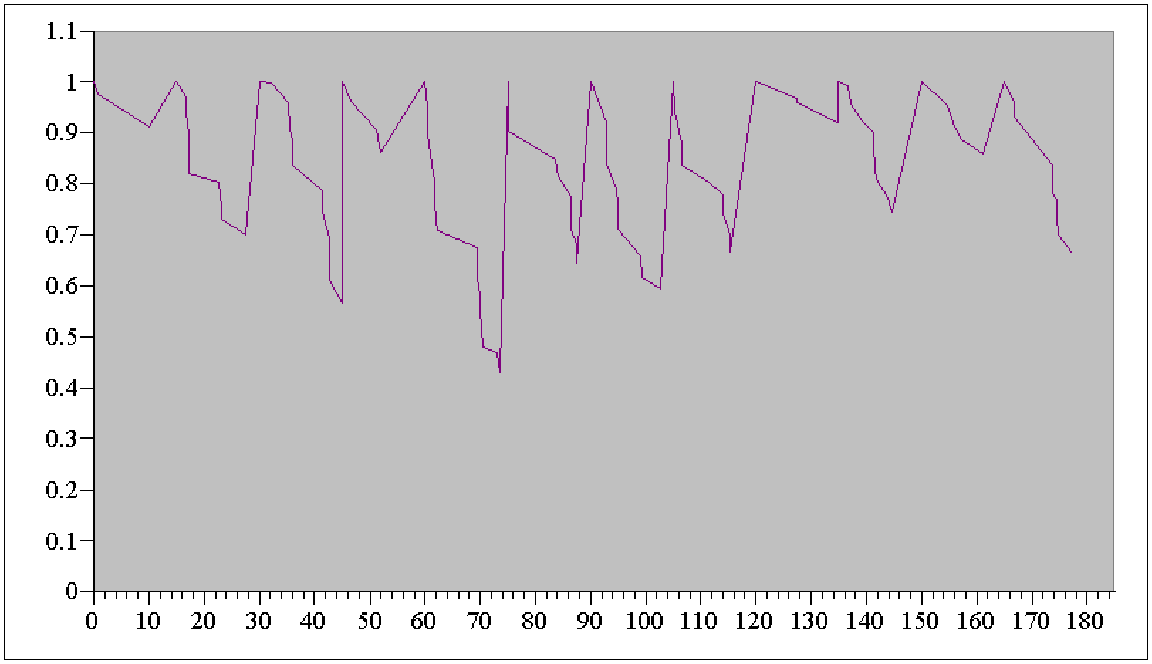


Figure 13 Periodic Cycle-Compound Poisson Dust Arrival

Both of the traditional periodic policy cases have been run for three different interval cycles, which are 7, 15 and 30 days period. Fixed cycle periodic cleaning policy with constant dust deposition is more expensive than the Poisson dust arrival for all the cases. As the constant dust accumulation of the periodic cycle, case 1, assumes the worse scenario, then the stochastic Poisson dust arrival of the periodic cycle, case 2, where dust accumulations follows a Poisson process. For the every-seven-days fixed cleaning policy, totaling 25 cleaning performances, which corresponds to \$0.398/day on average, whereas the Poisson demand yielded \$0.352 with the same number of cleaning requests. Under the monthly review policy, case 1, constant dust, cost $0.621; on the other hand, case 2, Poisson dust arrival cost $0.377. Table 11 summarizes the fixed policy models.

Fixed Policy Models	Cycle Length	Cleaning Orders	Average Holding Cost	Average Order Cost	Average Total Cost
7 Days /25 Cycle-Case 1	7	25	$0.120	$0.278	$0.398
15 Days /11 Cycle-Case 1	15	11	$0.283	$0.122	$0.406
30 Days /5 Cycle-Case 1	30	5	$0.565	$0.056	$0.621
7 Days /25 Cycle-Case 2	7	25	$0.074	$0.278	$0.352
15 Days/11 Cycle-Case 2	15	11	$0.158	$0.122	$0.280
30 Days/5 Cycle- Case 2	30	5	$0.324	$0.056	$0.380

Table 11 Periodic Cycle Policy with Different Cleaning Intervals

When we compare the results with corresponding adaptive policy models mainly referring to total number of cleanings we can clearly see that adaptive policy is superior to the periodic policy. Table 12 summarizes the corresponding adaptive policies.

Adaptive Policy	Target Clean. Level	Lambda Rain	Mean Rain	Std. Rain	Orders	Rains	Holding	Avg. Order Cost	Avg. Total Cost
λ0.02	0.75	0.02	0.15	0.1	11.5	5.4	$0.112	$0.128	$0.239
λ0.04	0.75	0.04	0.15	0.1	10.6	10.1	$0.107	$0.118	$0.225
λ0.08	0.75	0.08	0.15	0.1	9	19.1	$0.097	$0.1	$0.197
λ0.02	0.9	0.02	0.15	0.1	25.6	5.4	$0.043	$0.284	$0.328
λ0.04	0.9	0.04	0.15	0.1	24.8	10.1	$0.042	$0.276	$0.318
λ0.08	0.9	0.08	0.15	0.1	23.1	19.1	$0.04	$0.257	$0.297

Table 12 Adaptive Policies with Different Rain Arrivals

Together with the rain, the cost advantage of the adaptive policy is increased as well. Tables 13 summarize the cost savings of the adaptive policy over the traditional periodic cycle policy. Rows correspond to the adaptive policies with different rain arrival rate and target cleanliness factors whereas the columns represent the periodic policy with two different cases. Case 1 represents the worst-case dust deposition scenario under periodic policy where the everyday dust accumulation occurs at constant rate. Case 2 is more relaxed periodic policy where both the dust arrivals and dust intensities follow a Poisson process and normal distribution respectively. Cost calculations have been done with respect to average total cost values of the different scenarios of the adaptive and periodic policies taken from Table 11 and Table 12. To name an example calculations, when we compare the total cleaning cost of the adaptive policy with 0.02/day rain arrival rate with periodic policy under constant intensity everyday dust deposition, we can see that $0.328 average cleaning cost of adaptive policy is 18% more cost efficient than the $0.398 cleaning cost of periodic policy. If the periodic policy dust accumulation follows the same dust deposition of the adaptive policy, than the adaptive policy cost of $0.328 still 7% more cost effective than the $0.352 of the Poisson dust deposition periodic policy. As it is seen from Table 13, adaptive policies have greater cost savings over the periodic policy anywhere between 7% and 51% depending on different rain arrivals and dust deposition patterns.

	Periodic Policy Cases 1-7 Day Cycle	Periodic Policy Cases 2-7 Day Cycle
λ0.02/0.9 s- Adaptive	18%	7%
λ0.04/0.9 s- Adaptive	20%	10%
λ0.08/ 0.9 s- Adaptive	25%	16%
	Periodic Policy Cases 1-15 Day Cycle	Periodic Policy Cases 2-15 Day Cycle
λ0.02/0.75 s- Adaptive	41%	15%
λ0.04/0.75 s- Adaptive	45%	20%
λ0.08/0.75 s- Adaptive	51%	30%

Table 13 **Cost Savings Comparison between Adaptive vs. Periodic Cycle Policies**

EDS-Water Policy

Electrodynamic screens are one of the recently proposed solutions to the cleaning problem of the CSP parabolic trough reflectors, which continue to be developed and tested. Electrodynamic screen (EDS) is a transparent dielectric surface covered with electrodes, which charges the dust particles and remove dust form the reflector surface [22]. EDS technology mainly uses electromagnetic forces to push dust participles out of the screen surface and thus clean the reflector areas without using water or other additives. EDS technology is not available commercially yet, field tests are still being conducted. At the current level of technology, EDSs are successfully removing the 90% of the deposited dust within 2 minutes of operation using the relatively negligible power generated through collectors [22]. The lab results show that EDS system is still perform best when backup with water based cleaning. However, research to make EDS as a full replacement method of the water based cleaning continue and will likely to be achieved soon. Even with the current level of technology, an EDS cleaning policy is assumed the hold up to 90% of the Cleanliness Factor over the 90-day period under the same dust deposition conditions with the base adaptive policy. During the simulation, EDS cleaning operation cost will be neglected based on the research article as the power used by EDS is minuscule with respect to generation of the CSP plant [22]. During the simulation cleanliness factor continues to degrade up to 90% under daily operations of the EDS policy, due to technical limitations of the current state of technology and other environmental factors such as pre-existed dust on the mirror after EDS operations or other organic particles dropped besides dust deposition. When the overall cleanliness factor falls to 0.9 of the maximum cleanliness level, then the water based cleaning is requested with the traditional set up cost. The Figure 14 illustrates the 180-day simulation of the EDS powered hybrid cleaning operations.

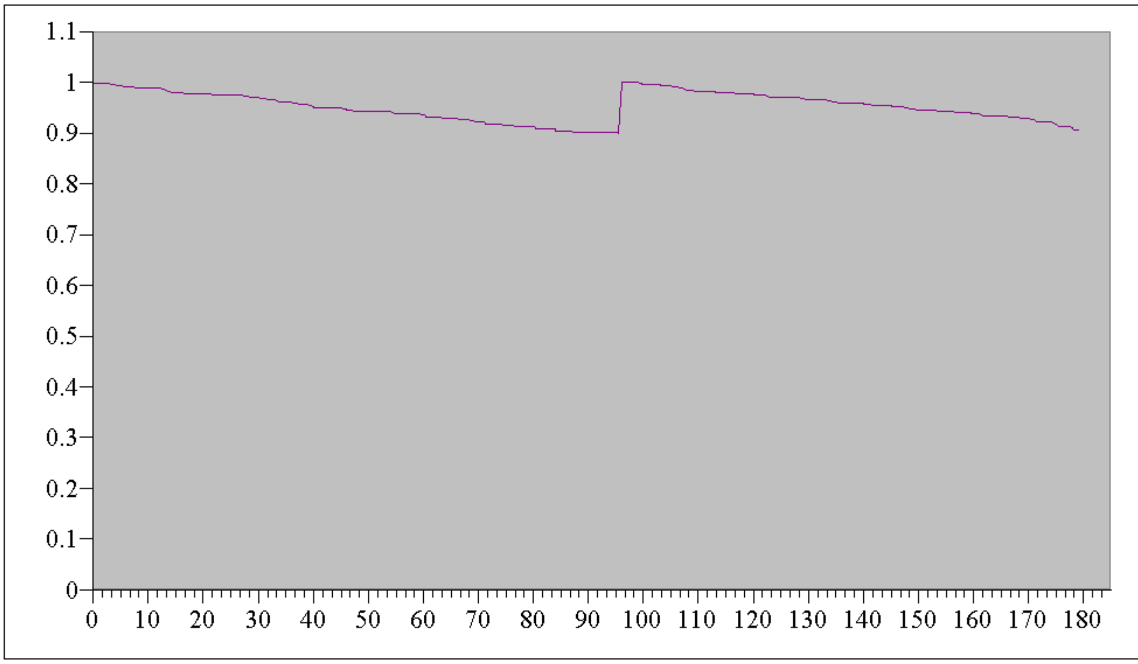


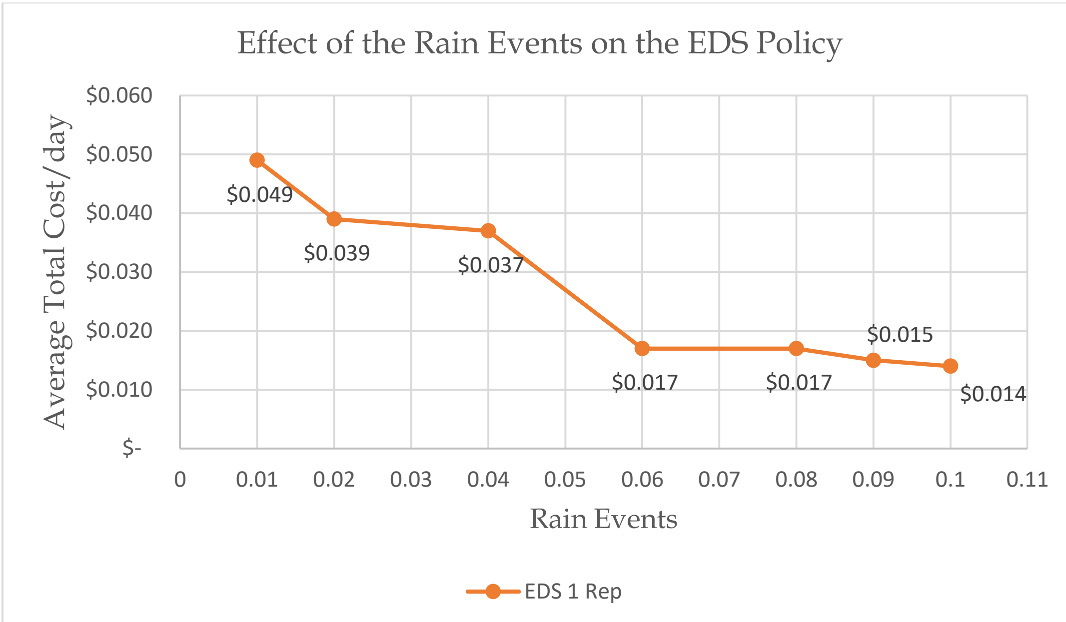
Figure 14 Cleanliness Factor with EDS and Water Based Cleaning

For this particular policy, effect of the rain events has been examined whether to see if the water based cleaning operation can be avoided with the support of Poisson rain arrivals. To do this, a rain arrival rate between 0 to 0.1, with 0.01 increment, has been subjected to cost function and the results have been summarized in table 14. The table shows the average total cost of cleaning with regards to rain arrival rate and total number of rain events during 180-day period. It is important the note that cost calculations do not account for the initial investment cost of EDS or other indirect costs, rather purely focus on the operational cost of the cleaning and holding cost of keeping Cleanliness factor less than perfect clean condition. More details about the level cost of the overall EDS system with respect to water-based policy can be found at [23]. Regular EDS performance sets the cost of cleaning \$0.057/day without the effect of rain arrivals whereas, rain arrival rate of 0.1 and 0.09 per day, which corresponds the 18.12 and 16.34 average rain events, have successfully cancelled the water cleaning and reduce the overall cost to $0.009/day. Table 14 on the next page, reveals the details of the analysis performed with one replication to show instant water cleaning decisions due to stochastic demand and the 100 replication shows the expected number events, cleanings and cost of operation. To make it practically useful, limit value of the expected water cleaning is set to 0.3. Below this limit system does not requested the cleaning and successfully maintain the Cleanliness Factor above target value without the additional water based cleaning, rather system is well enough to be cleaned by EDS under rain arrivals.

	Reps	Target Clean. Level, s	Rain Arrival λ	Rain Intensity μ	Rain Intensity σ	Setup	Holding	Rain Events	Water Cleanings	Avg. Ordering Cost/ day	Avg. Holding Cost/ day	Avg. Total Cost/ day
EDS 1 Rep Actual	1	0.9	0.1	0.15	0.05	2	1	14	0	$ -	$ 0.014	$ 0.014
	1	0.9	0.09	0.15	0.05	2	1	13	0	$ -	$ 0.015	$ 0.015
	1	0.9	0.08	0.15	0.05	2	1	13	0	$ -	$ 0.017	$ 0.017
	1	0.9	0.06	0.15	0.05	2	1	10	0	$ -	$ 0.017	$ 0.017
	1	0.9	0.04	0.15	0.05	2	1	5	1	$ 0.011	$ 0.026	$ 0.037
	1	0.9	0.02	0.15	0.05	2	1	2	0	$ -	$ 0.039	$ 0.039
	1	0.9	0.01	0.15	0.05	2	1	2	1	$ 0.011	$ 0.038	$ 0.049
	1	0.9	0	0.15	0.05	2	1	0	1	$ 0.011	$ 0.046	$ 0.057
EDS-100 Reps Expected	100	0.9	0.1	0.15	0.05	2	1	18	0	$ -	$ 0.009	$ 0.009
	100	0.9	0.09	0.15	0.05	2	1	16	0	$ -	$ 0.010	$ 0.010
	100	0.9	0.08	0.15	0.05	2	1	14	0.02	$ -	$ 0.012	$ 0.012
	100	0.9	0.06	0.15	0.05	2	1	11	0.03	$ -	$ 0.016	$ 0.016
	100	0.9	0.04	0.15	0.05	2	1	7	0.05	$ 0.001	$ 0.020	$ 0.021
	100	0.9	0.02	0.15	0.05	2	1	4	0.32	$ 0.004	$ 0.031	$ 0.035
	100	0.9	0.01	0.15	0.05	2	1	2	0.63	$ 0.007	$ 0.037	$ 0.044
	100	0.9	0	0.15	0.05	2	1	0	1.01	$ 0.011	$ 0.045	$ 0.057
EDS-100 Reps Practical	100	0.9	0.1	0.15	0.05	2	1	18	0	$ -	$ 0.009	$ 0.009
	100	0.9	0.09	0.15	0.05	2	1	16	0	$ -	$ 0.010	$ 0.010
	100	0.9	0.08	0.15	0.05	2	1	14	0	$ -	$ 0.012	$ 0.012
	100	0.9	0.06	0.15	0.05	2	1	11	0	$ -	$ 0.016	$ 0.016
	100	0.9	0.04	0.15	0.05	2	1	7	0	$ 0.001	$ 0.020	$ 0.021
	100	0.9	0.02	0.15	0.05	2	1	4	1	$ 0.004	$ 0.031	$ 0.035
	100	0.9	0.01	0.15	0.05	2	1	2	1	$ 0.007	$ 0.037	$ 0.044
	100	0.9	0	0.15	0.05	2	1	0	1	$ 0.011	$ 0.045	$ 0.057

Table 14 EDS Cleaning Policy with Rain Arrivals

Figure 15 below displays the effect of the rain events on the EDS policy with 1 replication and 100 replications. As the rain arrivals, following Poisson processes, instant simulation results may be slightly different from the multiple replications of the simulations, which is the case in this analysis.



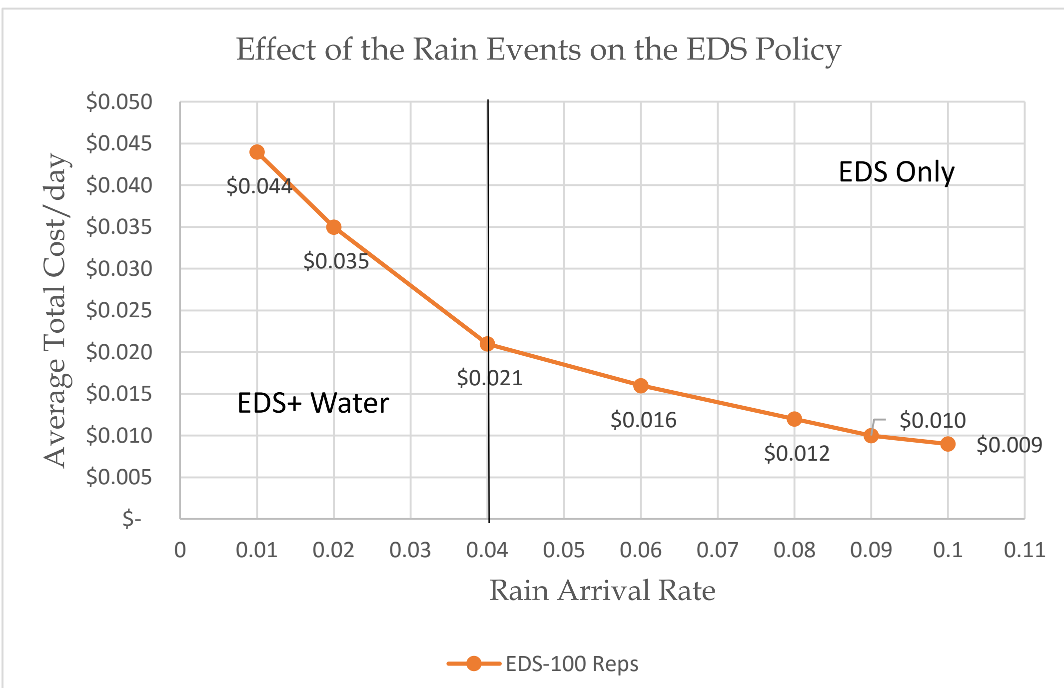


Figure 15 Effect of the Rain Events on the EDS policy with 1 and 100 Replications

The simulation has been run 100 times and expected number of water cleaning has been calculated. The cost function becomes smoother in which the effect of the rain arrivals can be seen the latter graph where the expected number of water cleaning absolutely cleared with the 18 and 16 rain arrival during the course of simulation. On average, any arrival rate greater than or equals to the 0.04/day would be enough to cancel water cleaning thus almost eliminates the operational cleaning cost of parabolic reflectors. For the practical implementation of the EDS policy, if the expected number of cleaning falls below 0.3, evaluator of the system avoids the water based cleaning. Thus, at least 7 expected rain events throughout 180-day cycle would be enough to cut down the cost of operation from \$0.057 to \$0.021, a highly significant saving equal to 64% of the base EDS policy.

CONCLUSION & DISCUSSIONS

The primary objective of this thesis is to study the effect of the non-deterministic dust and rain conditions over the cleaning operations of the parabolic trough collectors and CSP plants in general. An adaptive policy that continuously reviews the system and requests cleaning whenever necessary, rather than constant periodic review models, has been numerically examined with Arena Software package and results are presented in the last chapter. The conclusion drawn from that numerical analysis has been presented and the comparison of the traditional policy with adaptive policy has been made. After that, the conclusion and discussions about the EDS policy have been introduced.

Rain arrival rate analysis has shown that the increase rate of rain arrival reduces the average optimal cost of the cleaning, gradually reducing the cost 25%, from 0.256 to 0.193, when rain arrival hit 0.08 per day, which corresponds to 19 rainfalls through the 180-day period. Another conclusion drawn from the rain arrival is that the effect of rain arrivals over the optimal little s. Figure 16 shows that optimal target cleaning level, s*, increases with the rain at the beginning then decreases if the rain events become too frequent.

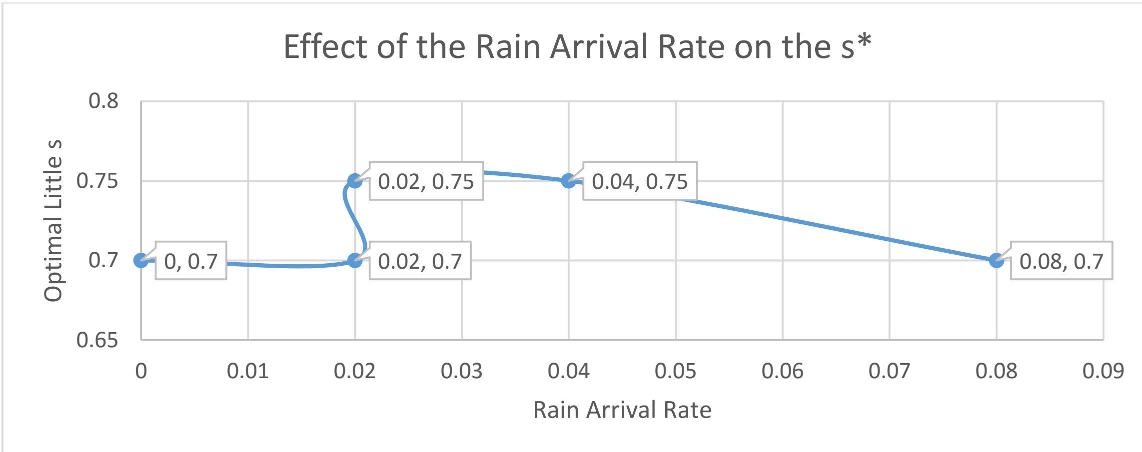


Figure 16 Effect of the Rain Arrival Rate on the Optimal Target Cleaning Level, s*

Dust rate analysis shows the seasonal and location based patterns of the dust depositions, which affect the overall cost of the cleaning. The slop of the cost rise is relatively linear until 0.8 cleaning points and increase exponentially after that especially for the regular and high dust arrival rates. It is been found that optimal target cleanliness level is reverse proportional with the dust arrival rate, at which higher rates decreases the optimal cleaning up to point, s*. Figure 17 illustrates the pattern of the target cleanliness level for different dust arrival rates. It could be drawn from the picture, adaptive policy becomes more tolerable to the dust on the reflectors to minimize the cost of cleaning if the dust frequency rate increases.

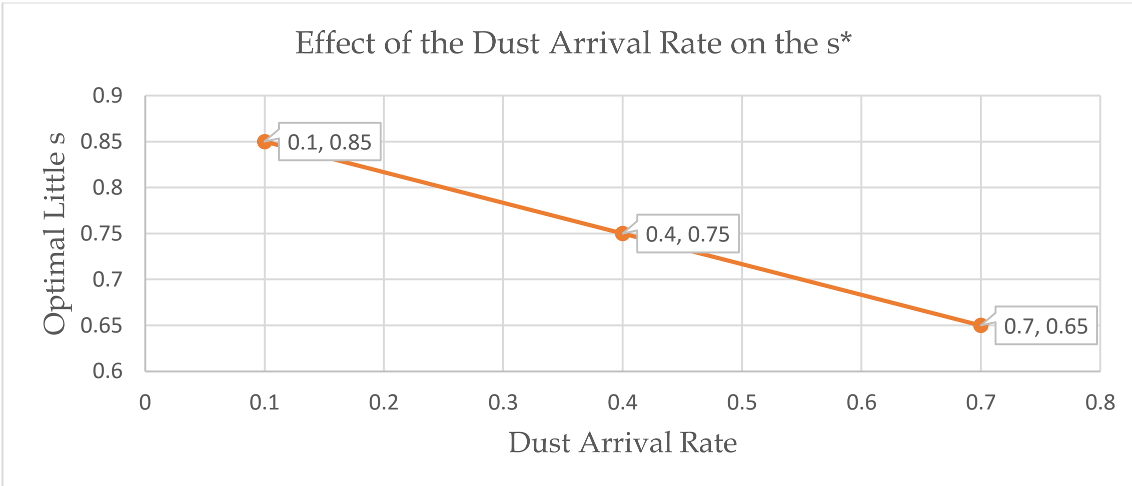


Figure 17 Effect of the Dust Arrival Rate on s*

When we look at the dust intensity analysis it could be concluded that the dust intensity has a similar effect on the cleanliness factor with more smoother and released effect. Figure 18 represents that as the dust intensity increases optimal order up to level decreases, while the cost of cleaning increases.

The additional cost comes from more severe dust deposition is less critical than the effect of additional dust deposition arrivals, which has been studied as effect of the dust arrival rates. Adaptive policy tends to be tolerable when the dust intensity increase as of dust arrival rate increases, yet the range of change for the dust intensity is limited to 10% rather than 20% change of that of arrival rate.

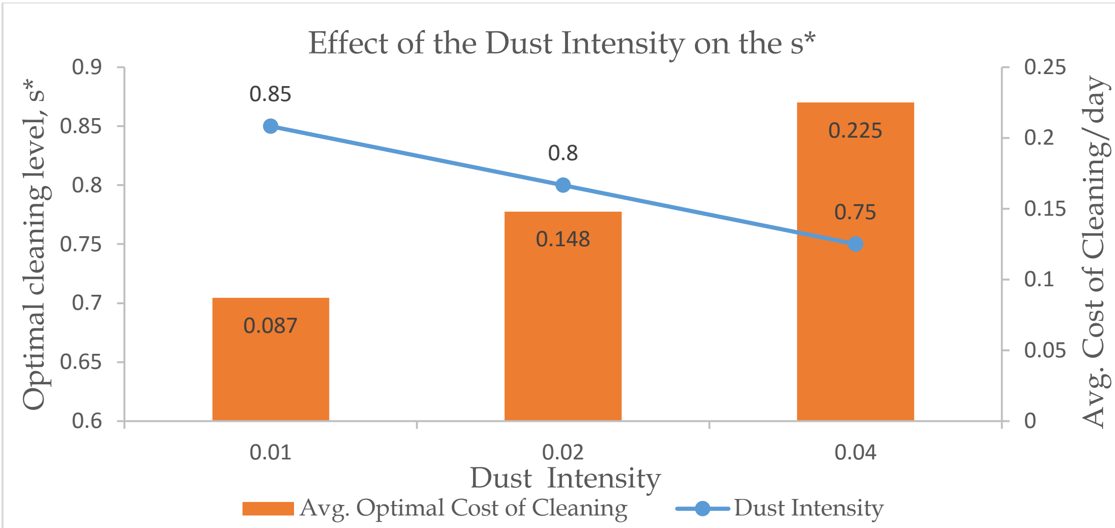


Figure 18 Effect of the Dust Intensity on the s*

The results of the rain intensity analysis is relatively packed and dense when we compare the results with the dust intensity analysis, which is reasonable as the difference between rain events and the dust events simulated is almost ten times for the base model of the adaptive policy. The effect of the rain intensity is more distinguishable at the lower cleaning levels of Cleanliness Factor yet merges toward the more demanding maintenance requirements of the higher threshold values of CF. In other words, one might conclude that all of the rain intensities are enough to maximize the CF if the target cleanliness factor selected greater than or equals to the 0.85. We can still observe the improvements of the intensities on the adaptive policy, which become more aggressive to dust deposition while minimizing the total cost of cleaning thanks to more intense rain events. Overall, for the given setup the effect of the rain intensity could be neglected when it compared with the effect of the rain arrival rates. However, furthers studies may reveal the more detailed impact patterns of the rain intensities even with lower proportions to the CF.

Setup Holding cost ratio analysis has been studied mainly to understand the weighted effect of the cost function parameters on the average cleaning cost and optimal cleaning reorder values of the Cleanliness Factor. Behavior observed during this analysis is that optimal target level keep reducing while set up/holding ratio increases and become no longer optimal. As the model request more cleaning to meet the demand of higher threshold limits, number of cleaning orders escalate, thus total the set up cost increases. As a result, minimization of the holding cost could no longer payoff the cost of additional cleaning to keep cleanliness factor as high as requested by reorder point means that relative benefit of power generation trough cleanliness of the reflectors cannot pay off the cleaning cost of reflectors. Figure 19 shows that the optimal target cleanliness level follows a downward trend while the setup/holding cost ratio increases from 0.5 to 2. As the setup holding cost ratio of 4 does not converge an optimal minimum cleaning cost we can not conlude the same results with the rest of the analysis.

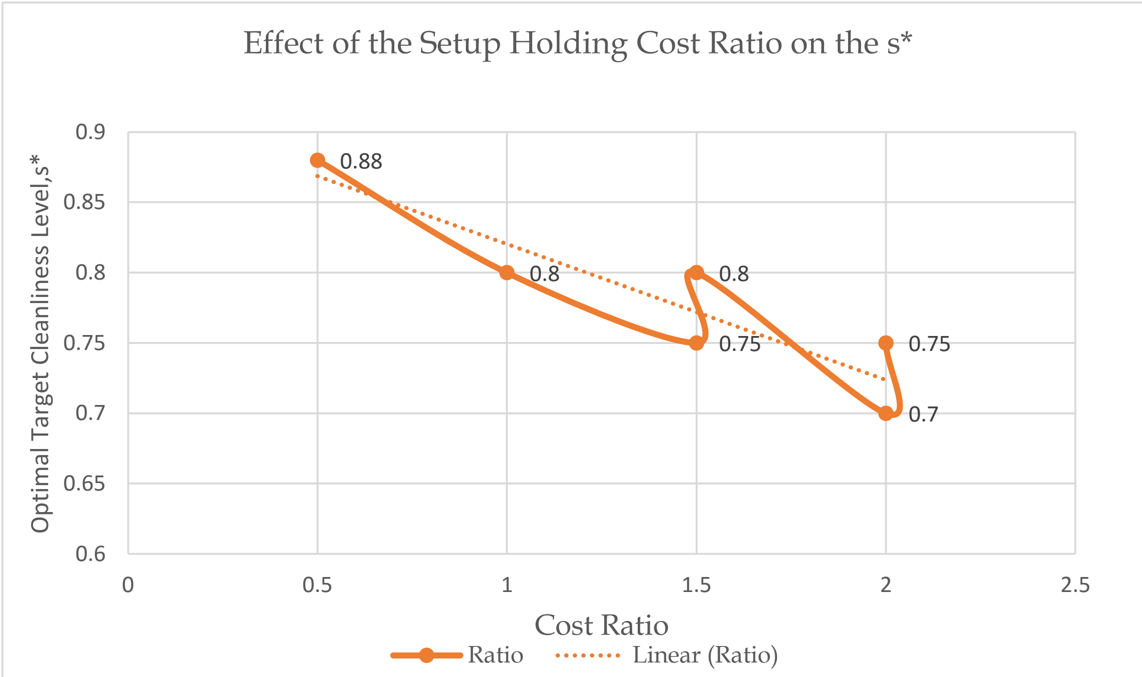


Figure 19 Effect of the Setup-Holding Cost Ratio on the s*

In summary, for the adaptive policy one can conclude that, increments of the rain arrival rate first increase the optimal cleaning value, then cuts back if the rain occasion becomes too frequent. In addition to that, increments among dust arrival rates, dust intensity and the setup/holding ratio follow the similar trends that gradually decrease the optimal cleaning reorder point. An interesting result is that the rain intensity of the arrivals have arguably neglected effect and merge to same optimal reorder points regardless of the current level of intensity. On the other hand, optimal average cost of cleaning drives down progressively with the rain arrival rates for all of the tested cleaning threshold points. Dust arrival rate has absolute drift over the total cleaning cost, which starts rising linearly then diverge exponentially. Dust intensity of the arrivals, increase the total cost smother than the dust arrival rate as oppose to rain intensity that has a negligible effect, probability because of the minority of the rain occasions. Setup/holding ratio has the similar effect with dust arrival rate that increase the cost first linearly then follows a rapid exponential trend. Table 15 below summarizes the findings of the adaptive policy analysis.

IF	THEN	
Increases	*Optimal Cleaning Reorder Threshold*	*Optimal Average Cost of Cleaning*
Arrival Rate	First increase then decrease	Decreases
Dust Arrival Rate	Decreases	First increase linearly, then exponentially
Dust Intensity	Decreases	Increases linearly
Rain Intensity	Negligible	Negligible
Setup/Holding Ratio	Decrease linearly	First increase linearly, then exponentially

Table 15 Summary of the Adaptive Policy Analysis

In light of this analysis, traditional periodic review fixed cycle model of current CSP plants has been studied and results are compared with the adaptive policy. As the fixed policy consider only fixed inter arrivals between cleaning cycles, instead of target cleanliness level, number of cleaning performed have been taken as a common ground for comparison. It has been concluded that, adaptive policy is always perform better and reach an impressive cost saving 51% of the corresponding fixed cycle policy together with the rain events. During this study only economic impact of the different polices has been considered. Environmental impacts e.g. water savings comes thorough adaptive policy or reduction of the Green House Gases emission have not been studied numerically. If further analysis will be done covering environmental improvements, the superiority of the adaptive policy over the periodic policy will be bolstered.

As an extension of the scheduling and cost analysis of the CSP plant, highly innovative and promising Electrodynamic screen method has been studied. Results show that if rain events happen as frequent as every 16 day on average, EDS operational cost decreased down to 29% of the original value, and what is more that when the rain arrives every 10–11 days EDS policy almost eliminates the cleaning cost of parabolic trough reflector solar fields.

EDS technology still continues to be developed with the aim of making EDS technology widely and commercially and economically applicable, and already started to be tested under real outdoor conditions. However, cost models and Cleanliness factor performance that subjected to our analysis still depends on many technological assumptions. Further studies need to be done to understand exact frontiers and limitations of the technology. On the other hand this study only consider rain events that support the Cleanliness Factor, yet it is known that depends on the prior conditions of the location and the duration of the rains, sometimes it may even degrade the cleanliness factor. This study might be expanded by modeling such rain events as well. In fact, it is vital to note that a CSP power plant requires certain amount of Direct Nominal Irradiance so as to generate power and keep operations profitable. If CSP power fields locations selected merely looking to the rain potential of the area to minimize O&M cost, this may create hardness to keep profitability of the plants at desired level to may end up with avoid main cause of the CSP, to collect sunlight and generate as much as possible. Even the proposed system covers night time rain arrivals thus partially eliminates the effect of cloudy weathers on the daylight DNI, further studies may need to be done to investigate rain arrival time during day and thus shows the rain-generation trade of the CSPs. This study also assumes that the unit setup and holding cost of the adaptive policy and traditional policy is same for both of the case, yet this may not be the exact same for the practical contract terms. As the adaptive policy requires stochastic cleaning operations, it is likely to be costlier than the pre-determined cleaning operations. If the calculations have been made considering these, more prices cost comparisons may have been calculated.

All in all, this study concludes that the adaptive policy of the cleaning operation minimizes the operation cleaning cost of the parabolic trough CSP solar fields compared to traditional practices, and shows the potential improvements of the schedule with the natural support of rain events.

APPENDIX

A-Arena Simulation Glossary

The aim of the Appendix-A is to give a glossary, which explains the Arena Program blocks used to create cleaning schedule simulation model. Rockwell Arana Simulation is a widely used package for the simulation of the complex systems and provides useful and user-friendly interfaces and subcomponents to create reliable simulation models. In this study, '*Blocks*' component panel of the arena simulation software is also used to simulate proposed model with respect to compound Poisson process and other distribution functions.

CREATE: The create block generates arriving entities to a process model [21]. Each entity is created as batch, which is determined by batch size expression. Consecutive entity arrivals with proper batch sizes are controlled by the inter arrival time expression. If there is a limit for maximum number of batches than the create block no longer become active. For the dust management and rain management models of the simulation create block generates rain and dust entities with respect to compound Poisson process. Each batch size of the arriving entities follow discrete cumulative distribution and inter arrival time of the each entity is exponentially distributed with reciprocal of rain arrival rate and dust arrival rate for the corresponding rain and dust management submodules. Simply, create block pick a sample from the Compound Poisson Process to determine stochastic dust or rain events. For the Cleanliness

Evaluation model, create block generates cleanliness factor evaluator every day to keep policy adaptive with the batch size of one at a time.

ASSIGN: The assign block allows the assignment of a value to a variable, user-defined entity attribute [21]. Arrived entities are updated with the expression of the corresponding assign block, which represent the value of the assign operation. In our model, assign block mostly used to update cleanliness factor level, which changes with dust arrivals and rain arrivals. Other usage of the assign block is to give and upper and lower limits to cleanliness factor, assign the required level of the cleanliness factor update comes with each cleaning operations.

BRANCH: Flow of the entities through the modules has been controlled and rerouted via branch block, which test the given conditions of the entity upon arrival and send it to corresponding next block [21]. Branch block at dust management modules set the current cleanliness level of the system, if the current state of the reflectors is already dirty, branch does not allow dust intensity to reduce cleanliness factor further. This is to comply module with the practical condition that if the system already lost reflectivity and reach minimum level of cleanliness already, additional dust deposition cannot degrade it more. If this not the case, means that dust deposition will continue to reduce cleanliness factor then branch block allow the arrived dust entity to affect and update the current cleanliness factor of the reflectors. Branch block at the Rain Management

Module also controls the effect of the rain intensity over the cleanliness factor. Upon creation of the rain arrivals, branch check whether the overall mathematical sum of the current arrival rate and the rain intensity is greater than or equal to 1. If this is the case, branch send entity to assign destination which limit magnitude to 1, which practically mean that cleanliness level cannot be greater than perfect clean state regardless of the type or intensity of the rain. If this is not the case branch block send the entity to second assign block where the entity value is added the current cleanliness factor and updated as new cleanliness factor, which is less than one. This means that arrived rain intensity improved the current cleanliness factor yet this is not enough to make reflectors perfect clean.

Cleanliness Evaluation modules uses branch block to check cleanliness factor every day and request cleaning whenever the level falls below target cleanliness level. Practically, system only orders cleaning whenever the level reaches the threshold.

DISPOSE: The *dispose* block immediately disposes of any arriving entities and updates the total number of entities pass through simulation [21]. In our cases, every dust, rain and evaluator entity created are only used once and at the end of process they leave the system. Total number of dust, rain and evaluator event are stored and updated after they disposed and leave the system.

COUNT: The COUNT block increments the counter specified by *Counter ID* by the value of the operand *Counter Increment* [21]. Cleanliness Evaluation modules uses count block to calculate total number of cleaning request is made by the system, then calculates the total fixed cost of cleaning.

B-Literature Review Tables

This appendix illustrates the executive summary of the literature review covered at the literature chapter of the thesis. Literature tables includes the corresponding article citation, intuition of the research, objective of the study, subject field, method used during analysis, achievements of the study and contributions to the literature. Last column summarize some of the comments made by the author of this thesis about the corresponding article. Following first three tables (Table 16-17-18) illustrate the literature of the CSP and Table 19 covers the literature studied for (s, S) Inventory Model with Compound Poisson Process demand.

Table 16 Literature of CSP (1/3)

REFERENCE	Problem/ Need to the research	OBJECTIVE	SUBJECT FIELD	METHOD	ACHIEVEMENTS	CONTRIBUTION	COMMENTS
Bergeron, K.D. & Freese J.M, 1981	need to find decision making process for cleaning stragety of parabolic trough solar collector systems	create detailed guidelines for cleaning process of the collector mirrors	Solar Collector Fields	litereture form the previous researchs & reports, expert and operator views	create a 9 step decision process for which to supoort decision process of the cleaning including clenaning intervals and cost of washing and others	upon development and commercial implemntations of the solar colelcter systems, this study is of the one of the first to put efforts to create a cleaning guidelines and practical critical points to keep solar collector fields economicall viable	dues to lack of expertise and new technological advancements major points of the guidelines depends on the assumption and even theese circumstances failure to strictly follow guidelines does not create much cost difference thus questions the effectivety of the cleaning guidelines
Cohen, G.E., Kearney D.W, Kolb G.J, 1999	final report on the O&M improvement program of the actual power plant at CA, USA	reduce O&M cost of CSP power plants	CSP	operational experience, testing of the equipments and new technology utilization	37% cost reduction in annual O&M , %33 water savings per Mwh generated and optimum solar field O&M plan proposed for the future applications	**1**-summarizes the real CSP power bank O&M projects' results and findings **2**-proposes O&M plan for the future solar field application	most water savings are not coming from the mirror cleaning operations thus report focus the overall structure of the O&M cost reductions by increasing operatinal effectivenes and deploying new technologies
El-Nashar, A.M, 2008	investigate effect of seasonal dust degration over the non-flat solar thermal collectors	to evaluate the effect of seasonal dust deposition and frequency of the cleaning on the solar field and overall perfermance of desalination plant	solar desalinatio n plant	experimental data from actual plant measurments are subjecto to matematical model of performance equations	**1**-transmittance drop rate vary seasonally: 2-4% for (nov-dec) and 6-16% for (may-agust) **2**-very dusty collectors (0.6 transmittence) reduce the production uto %40 of max **3**-weakly cleaning cycle is best for max water production **4**- water production vary by trasnmittence rate (1.8-2.7 L/MJ)**5**-power consumption of the plant is negatively correleted with the transmittence rate of reflectors	investigate the efect of the seasonal dust accumulation and the frequency of the collector cleaning thus contribute the litrature which does not count seasonalityt	**1**-different than the other examples where the aim of plants are to generate electricty yet the functionality of the solar colelctors and effect of the dust are the similiar to CSP plants. **2**-its finding may vary depends on the location

REFERENCE	PROBLEM/ RESEARCH INTUITION	OBJECTIVE	SUBJECT FIELD	METHOD	ACHIVEMENTS	CONTRIBUTION	COMMENT
rcia, F.A all ,2010	technical aspects of the water based clening studied to reduce cleaning costs	optimization of the water cleaning method to find most cost effective combination	parabolic trough collectors CSP	experimental design; 3 main parameters subject to optimization	**1**-best reflectivity and most cost effective results achieved with low washing water temp and medium water pressures **2-** water hardness as a measure of the quality does not necessary to be lower than 5ppm, (12 ppm water pressures gives similiar results with <5ppm waters). so cleaining cost involving demineralization can be avoided	optimized the technical aspects of the water based cleaning which has not yet been studied in a detailed way before	does not establish a matematical expression for the cost analyissi regarding the three technical parameter of the water based cleaning
urchi,C ,2010	need for the update NREL's cost assesmets techniques that stands back in 1999 does not accurately represents 2010s expenses	help create a model framework that would allow SAM users to look at the cost impact of individual components of a typical parabolic trough plant (paraphrase needed)	parabolic trough collectors CSP	conceptual design and cost assessments of the parabolic trough plants with 2 different technological set-up (wet-cooled and dry-cooled)	comparison between two models (dry and wet cooling)reveals that dry cooling set-up requires more solar field areas and installation cost than the wet-cooling yet the overall LCOE for both is relatively similar as dry-cooling design generates more annual power **2-** water consumption of the dry set-up is 93% lower than wet design yet the specific water consumption for mirror cleaning more than wet cooling due to lower efficiency of dry cooling **3-** cost model lacks some of the indirect and owner's cost and SAMS model takes O&M cost as 25% of the total direct and contingecy costy (not studied explicity)	create a excel detachable spreadsheet that allow user to manipulate component based cost of the plants regarding technological differences, commodity prices or other user related local factors needs to tailored for specific	**1**- model does not have a detailed O&M cost plan other than a roll-up of O&M costs **2-** spreadsheet of the cost model can be added to Excel so support a widely used environment for end users

Table 17 Literature of CSP (2/3)

REFERENCE	PROBLEM/ RESEARCH INTUITION	OBJECTIVE	SUBJECT FIELD	METHOD	ACHIVEMENTS	CONTRIBUTION	COMMENT
Garcia, F.A et all ,2013	negative effect of the dust accumulation on the power generation and need for minim of cleaning cost of the CSP plants	measure the effectiveness of the different cleaning methods in semi-arid CSP locations	CSP	experimental test design of the cleaning methods at real outdoor conditions during 2 years	**1**- 0.2 % is the effect of the detergent with 3 pass high pressure water cleaning (not effective) **2**-a pay of between number of cleaning passes and reflectance rate should be considered **3**-most effective cleaning method is demineralized water with brush (steam based method ineffective) **4**-deluge waterfalls would be enough to recover 0.9 of max reflectance without artificial cleaning	effectiveness of the natural rainfall over as a cleaning methods is observed 2-detergent additive to water cleaning found ineffective under 3 passes cleaning method	**1**-critical as expliticy states the effect of the natural rainfalls on the mirror reflectance as a proven method cleaning **2**-mentions the ineffectiveness of the detergent additive which might help reduce cleaning cost and minimizes environmental effects of cleaning
Bouaddi,S et all, 2017	to understand soiling behavior so as to optimize cleaning strategies for local conditions	study soiling patters of widely used silvered mirrors and innovative aluminum based reflectors	feasability of CSP w.r.t soiling	data from experimental design is subject to dynamical factor analysis (DFA) and time series	**1**-under wet condition soling rate in aluminum mirrors is worse than glass ones **2**-deluge rains are enough the recover especially glass mirros but also some type of aluminum reflectors **3**-soling rate decrease more dramatically at perfect cleaning mirrors than partially soiled ones **4**- DFA models soiling rate with two common trends yet model does not improve with weather information such as wind speed, humidity and rainfalls	reveal the effect of the rainfalls on the soiling rates among different reflector technologies, show the almost perfect cleaning effect of the heavy rainfalls on the widely used mirrors	further research on the effect of rain event and and characterization of the soiling patters of the different technologies

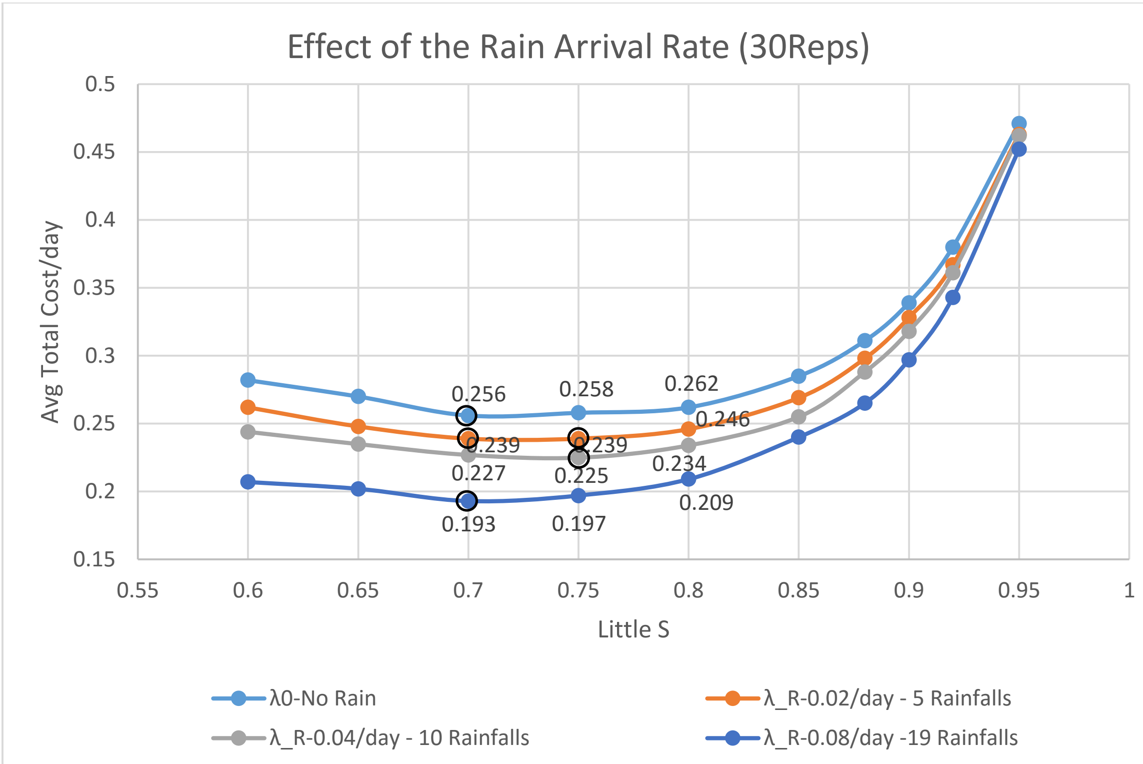
Table 18 Literature of CSP (3/3)

REFERENCE	INTUITION	OBJECTIVE	SUBJECT FIELD	METHOD	ACHIEVEMENTS	CONTRIBUTION	COMMENTS
Archibald, B. C. & Silver, E.A, 1978	focus the special case of the inv. model with arbitrary interval and quantity distributions of the demands	**1**-show existance of optimal. policy for the single product cont. review compound Poisson demand systems **2**-develop formulation to calculate the cost of (s, S) policy **3**-study the decision rules of the erratic demadn inventory systems	inventory management	algorith to find optimal values of cost function, numerical study with 500 sample	**1**-cost function relatively insensitive to variations of the s and n value **2**-optimal control parameters (s*, S*, n) sensitive to pmf of demand transactions (more with erratic demand)	easy to follow algorithm to find an optimal policy for continuous review(s, S)	enhanced existed problem to cover special cases
Tijms, H.C & Groenevelt,H, 1983	difficulties of defining shortage cost while optimizing (s,S) policy	to find reorder point of the periodic inventory systems to the general class of (s, S) inventory systems covering continues review case	inventory management	direct approach to find re-order point which is simpler than the previous approx.	simple approximations for reorder points of (s, S) policies calculated with 2 moments approximations of the reorder point equations (normal or gamma fit depends on the demand dist coefficient	fist time tractable algorithms for cont. review (s, S) policy.	depends on the several assumptions including demand transactions and on hand stocks
Zheng, Y. and Federgrun A., 1991	optimal policy computatuions of existed algorithms are computationaly expensive so less practical and rarely applied	provide an algorithm to compute optimal policies for (s, S) inventory systems in a less expensive, simple and provable way	inventory management	iteration of the full enumeration of the two dimensional grid on the (s,Δ) to find s* and S*	**1**-algorithm, which could be applied to both periodic and continues review systems, has gives the tighter upper and lower values for (s*,S*) than existing algorithms **2**-computational efforts to find optimal (s,S) policies less demanding and tied by 2.4 times of that of single item policy	provide new algorithm to compute optimal (s,S) policy, which is simple,easy to prove and better than the existing alternatives	applied mainly to periodic review systems and gives less insight for the further details of the continous review models

Table 19 Literature of (s,S) Inventory Policy with Random Demand

C-Test of Robustness

The analysis of the simulation has been run several times to minimize effect of the initial parameters and outliers. Numbers of replications have been varied from 30 to 100 per analysis. In this appendix, effect of rain arrival rate test has been run 1000 times to investigate the robustness of the simulation. Computational time of the simulation increased significantly to several hours when all the 40 instants of the rain arrival rate runs for 1000 reps. Error rates of the rain arrival rate raised to 2.59% for the 0.7 target cleanliness level of the 0.08/day rain arrival rate. Mean error rate of the all analysis is 0.18% for all of the target cleanliness level and rain arrival rates, which shows that the 30-rep simulation is well enough and thus provide efficient computation of the simulation. Graphics 20 illustrates the rain arrival rates for 30-rep and 1000-rep respectively. When we look at the behavior of the optimal target cleanliness level, we still observe that optimal target level tends to decrease if the arrival rate increases continuously. Optimal target cleanliness level starts at the 0.75 target level instead of 0.7 target cleanliness level of the 30 rep results and reaches dual optimum at 0.08/day pointing out the decrease trend of the target optimal level. Further analysis may need to be done to better understand the behavior of the optimal target level, which minimizes the total overall cost of cleaning with respect to changes in rain arrival rate.



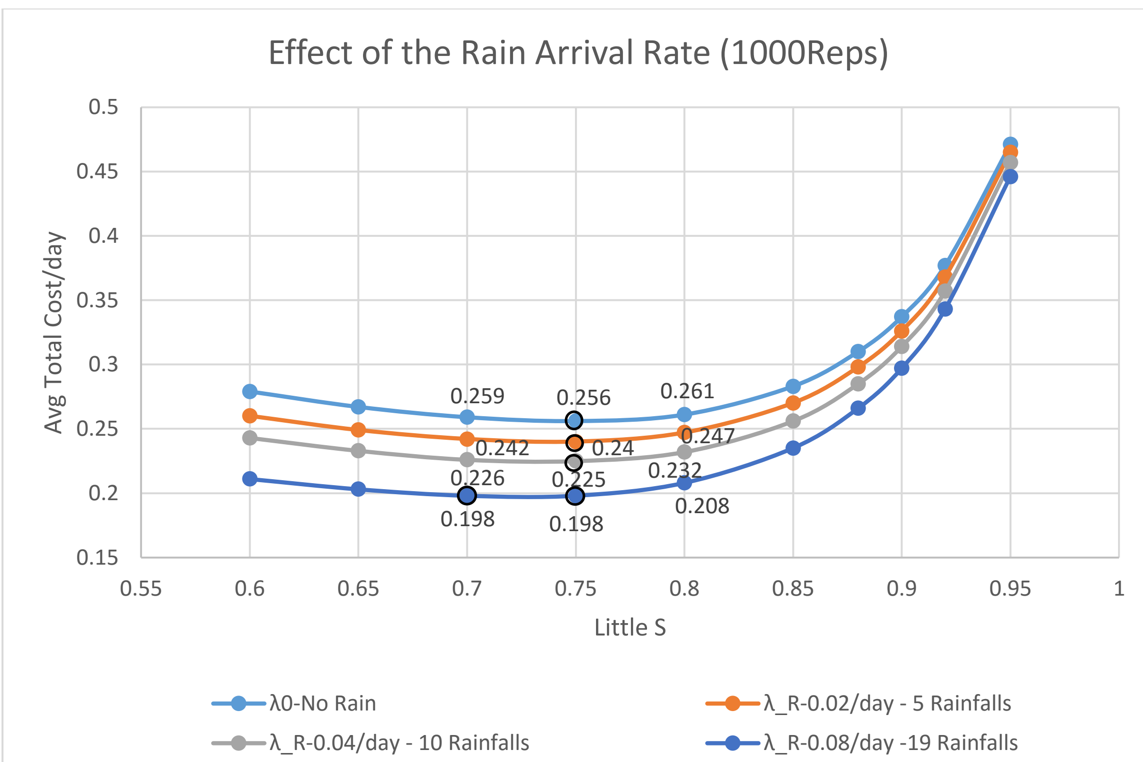


Figure 20 Rain Arrival 30 Reps &1000 Reps

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CURRICULUM VITAE

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