Exploitation Efficiency System of Crane based on Risk Management

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Abstract: The subject of the paper is the exploitation efficiency system of overhead type cranes operating in critical systems, results implementation the control risk management and maintenance scheduling processes. The study case of the paper is a hot rolling mills system of a steel plant with critical overhead cranes operating with hazard conditions and continuous operation. The model output is an optimal overhead cranes maintenance scheduling distribution minimizing the production line risk stopped and the model input is a digital database structure with historical information related with the operation, maintenance, logistics and management process of the overhead cranes in the hot rolling mills plant. The transfer function is a stochastic non-linear optimization model with bounded constraint that assess a risk global-system indicator based on Monte Carlo simulations.

1 INTRODUCTION

Today's industry has high levels of automation and complexity, therefore, decompound the Lego system into critical pieces simplifies the problem and gives us the opportunity to focus on a specific process.

The process of degradation is inherent in the technical system; consequently, control risk management and maintenance scheduling processes are increasingly relevant, and the human decision-making process behind is a target to improve.

Human decision-making process behind of the *control risk management* and *maintenance scheduling* processes is the coordination of components maintenance and/or replacement that make up the system but maintaining risk holistic and/or clustering objectives defined by the decision makers.

Coordination of larges combinations, meaning larges systems, can be a complex problem and humanly dreadful to find a faster optimal solution. Mathematically speaking is a nondeterministic polynomial time *NP*-complete problem.

As we know, for the search of optimal solutions, it is needed first, to model the system and its possible operational scenarios, to make a coherent coordination. Reason why, software, tools, robots, platforms are needed to perform this coordination duties efficiently.

In the field of *control risk management*, we found the closed-loop engineering (CLE) framework introduced by (Barari et al., 2009) as a well-stablish approach for robust and coherent coordination.

Strong references of CLE implementation are (Gholizadeh et al. 2020) for operational and tactical decision-making levels to configure a coordinated supply chain network, (Jerome et al. 2020) for integration of production scheduling decisions within a dynamic real-time and (Rui et al. 2020) to assess the dynamic reliability of repairable closed-loop systems with the consideration of uncertainties. All of them are examples of platforms to support robust and coherent coordination duties.

Following the same research line, in this paper, we study the *control risk management* and *maintenance scheduling* processes for overhead cranes operating in a steel plant. An innovated exploitation efficiency system of crane based on risk management is proposed to simulate the same process performed in the time real, but in this case, an optimization algorithm chooses the best maintenance schedule given the historical degradation data of the previous process as a result of machine learning analysis, and provides the feedback to the entity manager as a

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closed-loop control system. Among the cases cited, the reference (Rui et al. 2020) maintenance decisions oriented with a novel non-probabilistic reliability assessment approach is an example close to the proposal in this paper but in a different system.

Figure 1 describes the block diagram of the engineering solution proposed, called in this paper as Integrate Maintenance-e (IMe), e- referring to electronic or digital.

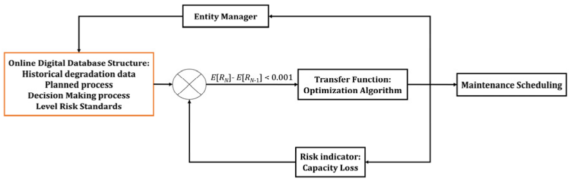

Figure 1: Risk based Maintenance Management Efficiency Control System.

In the presented model, the *control risk management* effectivity depends on the *maintenance scheduling* optimization. By nature, in the literature, this process is an open problem because engineering systems increase their complexity and variety every single day and new researches are needed to fill the gabs of the challenges.

Maintenance scheduling as a general problem, can be decomposed essentially by hierarchical levels, holistic objective (referring to global or integrated strategies) or multi-objectives (referring to decentralized strategies), and optimization criteria cost, reliability, or hybrid approach. Examples are cost-holistic (Akaria et al., 2019), cost-multi-objectives sequential (Briskorn et al., 2019) and holistic-reliability approach (Luo et al., 2019). For any of the cases, the problem is to find the best scheduled maintenance sequence of actions for each component considered in the system.

Generally, the objectives and restrictions are not well defined because depends on the individual system requirements. However, as a consensus, the optimization problem is defined as a multi-criteria combinatorial problem of non-linear objective functions with constrains (adding by us stochastics), and the problem objective is to determine the timing and sequence of the maintenance tasks periods of each component analysed. Therefore, the variables x in a maintenance scheduling problem is represented by the start time of the maintenance tasks for all the component considered.

Especially, the paper is focuses on defining the exploitation efficiency system based on risk management for overhead cranes under operation into the steel plant, and in a specific scenario description as an application example. The idea is to contribute with an example of overhead cranes adaptation to the digital industry and with a clear union of *control risk management* with *maintenance scheduling*.

The motivation of the investigation starts with the identification of organization issues in the dedicated maintenance department of the steel plant, which is focusing on cranes operation into the continuous transportation process in the hot rolling mills system. In this system, overhead cranes are critical devices, because in case of failure or maintenance the production line can stop.

The department have a risky situation also when a scheduled maintenance of selected cranes (existing as hot redundancy) is performed and at the same time an unexpected fail of cranes in use in the system are reported.

In practice, we consider a set of cranes in the operation process of the plant. We learn about the results of technical degradation of cranes under the operation processes, implementation results of dedicated to cranes maintenance focused procedures, as well as the existing environmental conditions and applied plant operation strategies.

The presented exploitation efficiency system based on risk management for proper engineering decision making and controls, considers the plant operation strategies. The system platform helps also to adapt crane maintenance processes to the existing operation problems and events and available resources, as well as unexpected critical events into the hot mill system.

The IMe platform supports decision-making processes aimed at minimizing the risk of the operational safety of cranes and the risk of losing their operational reliability, as a result of the degradation of the structure and utility functions of devices and the possibility of a combination and association of events and failures resulting in a safety hazard under operation processes.

In our case, maintenance-task distribution or maintenance scheduling solution implemented is a holistic-reliability approach.

The approach was selected holistic for an easy interpretation of the maintenance impact on the system by the entity manager (unique indicator), and reliability, because overhead cranes in a steel plant are critical devices working in a continuous process, by construction, the system must be reliable.

In this paper, the approach selection is driven by individual system requirements and the contribution is strongly guided by the CLE framework (Barari et al., 2009).

Conceptually, the proposed model considers two layers (live and digital) guided by independent processes that are eventually are combined by the platform.

Live layer presents manufacturing process in the real time, representative by dedicated exploitation data. Historical data from the crane operation process is supplemented with current data obtained from the transport process carried out by cranes, which are available results with the use of sensors.

Digital layer based on Digital Twin (DT) processes replaces human decisions making by risk managements tools, incorporating optimization of the decision making involved.

The first process concerns the registration of the process of technical degradation of cranes exploitation parameters and losses their functional functions, because of the implementation of specific transport processes.

The second process is oriented towards planning service processes with the use of specific limited and available resources, their correlation with planned overhauls of a technological manufacture line and their adaptation to the occurring unplanned events and expectations. The process of planning service and maintenance processes is accompanied by an optimization process focused on the planned efficiency of the production system and minimizing possible production losses.

Such decision supporting model platform, based on parallel real and digital processes, helps to design optimal maintenance strategies dedicated to the selected cranes, including type of the activities and timetable, and needed resources. Is holistic, safety and reliability oriented, includes quality and quantity cranes representatives' parameters for decision making processes.

In practice, the input of the model is a database structure created for maintenance purposes based on historical degradation data of all the system components, previous planned process, system structure, etc., collected by SCADA (Supervisory Control And Data Acquisition) and SAP (Systems, Applications and Products in Data Processing) systems, in fact, available historical information related to the maintenance scheduling management process.

The output of the model in our case is to provide to the entity manager a faster and optimal online decision-making process as a closed-loop control system (CLCS).

Once the maintenance scheduling management process is optimal (supporting by live and digital layers), as a result, the holistic operational efficiency in the plant increases. In the following sections, the model is fully described using a specific scenario.

The document is organized as follows; firstly, the mathematical formulation of the optimization problem is presented with the constraint set and the flow diagram, as well as all the equations and assumptions of the proposed model organized in subsections. Following the same idea, in next sections the scenario (parametrization) and methods (solution) are described, discussed, and validated. Finally, some important conclusions are drawn to highlight potential outcomes in this research area.

2 IME-PLATFORM: MATHEMATICAL MODELLING

The proposed model aim is to minimize the expected value of the convolution function, between the overhead cranes loading system capacity distribution function of the steel plant impacted by maintenance scheduling and the necessary load capacity distribution function of the production line. The model is defined below:

$$\begin{array}{l}
\quad \min\{E[R]\} \\
\text{where:} \\
\quad R \quad \rightarrow \quad f(X,Y) \\
\quad X \quad \rightarrow \quad f(t, LC_i, \ldots) \\
\quad LC_i \quad \rightarrow \quad f(t, TTM_{i,k\neq 1}, TDM_{i,k}, x, \ldots) \quad \text{with} \quad x = TTM_{i,1} \\
\text{subject to:} \\
\quad 0 < TTM_{i,1} < \text{Simulation Window} - (TTM_{i,1} + TTM_{i,k\neq 1} + TDM_{i,k})
\end{array} \tag{1}$$

The stochastic non-linear optimization model with bounded constraints proposed for the overhead cranes' maintenance scheduling problem solution in the steel plant present only continuous variables $x = TTM_{i,1}$ (time to maintenance) and is defined in the model constraint intervals. The independent variable of the objective function to be optimized $x = x_1, x_2, \ldots, x_{NMi}$ depends on the quantity of maintenance task NM_i to be coordinated for each overhead crane.

The optimization variables are only the start times for the first maintenance of each overhead crane $TTM_{i,1}$. Once $TTM_{i,1}$ is established, the remaining $TTM_{i,k\neq 1}$ are calculated adding the corresponding maintenance intervals, which are invariable and depends on the operation time between two consecutive check-ups.

Figure 2 shows the conceptual flow diagram implemented to solve the problem. The flow diagram is linear and only has two conditioning moments, first one to guarantee the simulations error criterion, and second one to guarantee the best solution of all the scheduling proposals evaluated.

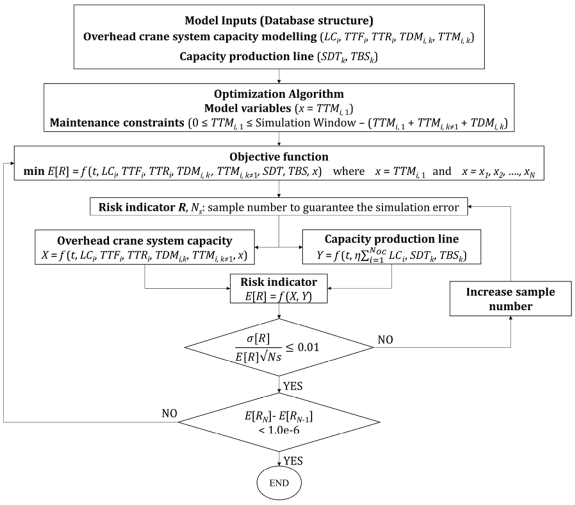

Figure 2: Flow optimization model.

The problem is solved as follows: the optimization algorithm proposes a set of $TTM_{i,1}$ and N_s Monte Carlo simulations are performed to determine N_s values of risk (r_1, r_2, …, r_{Ns}). The Risk mean $E[R]$ and variance $V[R]$ are determined from (r_1, r_2, …, r_{Ns}) and the error criterion is checked. If the desired error is not achieved, N_s is augmented and the Monte Carlo simulations are repeated for the same set of $TTM_{i,1}$. When the desired error is achieved the process is repeated for another set of $TTM_{i,1}$. This is done several times (1, 2, 3, …, N) determining decreasing values of Risk mean $E[R_1]$, $E[R_2]$, …, $E[R_N]$. The set of $TTM_{i,1}$ leading to the lowest Risk mean ($E[R_N]$) is the solution.

The optimization model construction formalized in this section is structured in two steps. First one, the production-line-capacity and overhead-cranes-capacity stochastic mathematical models for a steel plant are defined. The model used for the overhead cranes has two reliability states and considers random faults intrinsic to these systems, faults repair times and operation standards. Second one, the Monte Carlo simulation model used to estimate the risk indicator (Capacity Loss) is formalized.

2.1 Production Line Capacity Modelling

In a continuous production process, always the devices target function, at all the hierarchical levels is to be available. Redundancies for critical devices are crucial in continuous process to obtain high reliability performance, therefore, as an example the steel plant have more overhead cranes than needed.

In this paper based on a steel plant scenario, we define the production line capacity dependent on the total overhead cranes loading capacity of the system. In the proposal model, we call this parameter η - *Production line efficiency* because is an indicator between [0, 1] and measures the relation between minimum availability of overhead cranes required to secure the production line and total overhead cranes loading capacity of the system.

In addition, for maintenances purposes also, but not related with the overhead cranes system, the steel plant need to stop the production line N_{SPL} times, therefore two additional parameters STD_k (stooped time duration) and TBS_k (time between stooped) are introduced into the model. As a result, the production line capacity is defined as follows:

$$Y = f(t|\theta) = \begin{cases} \eta\sum_{i=1}^{N_{OC}} \overline{LC_i} & \text{if} \quad t < \sum_{k=1}^{m} TBS_k + \sum_{k=1}^{m-1} STD_k \\ 0 & \text{if} \quad \sum_{k=1}^{m} TBS_k + \sum_{k=1}^{m-1} STD_k \le t < \sum_{k=1}^{m} TBS_k + \sum_{k=1}^{m} STD_k \end{cases} \tag{2}$$

where t is time, θ is a set of parameters, in this case $\theta = \{\eta, \overline{LC_i}, TBS_k, STD_k\}$ and $m = 1, 2, 3, …, N_{SPL}$.

2.2 Overhead Cranes Modelling

Overhead cranes operation is continuous, eventually fails and is repairable. This random behavior can be described from distribution functions fitted to historical degradation data. Considering the operation effectiveness of the overhead crane, in this paper, we fix that the system and its components have two states z = 0, 1 and between them transition rates are defined depending of the distribution function selected in the simulation approach. The probability of moving from one state to another depends on the failure or repair rate of each overhead crane.

In the two-state model, the overhead cranes are considered fully available (z = 1) or totally unavailable (z = 0). The stochastic loading capacity LC^D_i at the time instant t of an overhead cranes i is determined by the $TTF_{i,k}$ (time to failure), $TTR_{i,k}$ (time to repair) and $\overline{LC_i}$ (nominal loading capacity). The parameters allow to simulate with (3) the behavior of LC^D_i generating k-th independent random numbers from distribution functions fitted to historical degradation data. Therefore, the model proposed to simulate the stochastics overhead cranes loading capacity is defined below:

$$LC_i^D = f(t|\theta) = \begin{cases} \overline{LC_i} & \text{if} \quad t < \sum_{k=1}^{m} TTF_{i,k} + \sum_{k=1}^{m-1} TTR_{i,k} \\ 0 & \text{if} \quad \sum_{k=1}^{m} TTF_{i,k} + \sum_{k=1}^{m-1} TTR_{i,k} \le t < \sum_{k=1}^{m} TTF_{i,k} + \sum_{k=1}^{m} TTR_{i,k} \end{cases} \tag{3}$$

where t is time, θ is a set of parameters, now $\theta = \{\overline{LC_i}, TTF_{i,k}, TTR_{i,k}\}$ and m = 1, 2, 3, …, N_{RNi} knowing that N_{RNi} depends on the *Simulation Window* used in the optimization model. The k-th independent random numbers generated from distribution functions fitted to historical degradation data guarantees the follows restriction:

$$\sum_{k=1}^{m} TTF_{i,k} + \sum_{k=1}^{m} TTR_{i,k} \ge \text{Simulation Window} .$$

On the other hand, one of the factors that affects the overhead crane loading capacity, is not stochastic and is not considered a random phenomenon, it is type maintenance process, and in this paper, we assume independent from the previous one during the simulation. The maintenance is contemplated within the strategies of a steel plant because it guarantees cranes life cycle. Maintenance is the activity designed to prevent failures in the production process and in this way reduce the risks of unexpected stops due to system failures. In a steel plant, to perform some maintenance tasks it is necessary that the overhead crane does not work, and this causes Capacity Loss in the steel plant. Due to this reason, it is advisable that this maintenance task be carried out at the time of the year where the least frequency of system potential failure exists, so that equilibrium and adequate environment are secured in the steel plant. To consider this effect, in this paper the parameters $TTM_{i,k}$ (start time to maintenance) and $TDM_{i,k}$ (time duration maintenance) are introduced in the equation (4), then we combine the equation (3) and (4) using junction symbol & representing the AND logic, as we show below:

$$LC_i^M = f(t|\theta) = \begin{cases} \overline{LC_i} & \text{if} \quad t < \sum_{k=1}^{n} TTM_{i,k} + \sum_{k=1}^{n-1} TDM_{i,k} \\ 0 & \text{if} \quad \sum_{k=1}^{n} TTM_{i,k} + \sum_{k=1}^{n-1} TDM_{i,k} \le t < \sum_{k=1}^{n} TTM_{i,k} + \sum_{k=1}^{n} TDM_{i,k} \end{cases} \tag{4}$$

where t is time, θ is a set of parameters, now $\theta = \{\overline{LC_i}, TTM_{i,k}, TDM_{i,k}\}$ and n = 1, 2, 3, …, N_{MTi}; and as a combination consequence of both process $LC_i = LC^D_i \,\&\, LC^M_i$ knowing that the junction symbol & is used for the AND logic. As a modelling result, the LC_i variable consider both process, degradation (D) and maintenance (M).

Once we know the LC_i for each overhead crane, we use reliability block diagrams to compose the system loading capacity. A technical complex system structure can be reduced in a series-parallel reliability block diagram, and the steel company is not the exception. Usually, the steel companies have huge warehouses, and inside overhead cranes are installed, therefore the series-parallel configuration of the cranes follows the structure of the warehouse. Based on the configuration of the warehouse is possible built the system block diagram, and as a result, the system simulation process is consequent with the relation between cranes.

In order to consider the block diagram structure of the system, we propose a simple rule in this paper. Following the generic series-parallel structure, when two or more overhead cranes are in series ($Crane_1$ & $Crane_2$ & … $Crane_N$) the junction symbol & is used for the AND logic, while the symbol || is used for the OR logic when the overhead cranes are in parallel ($Crane_1$ || $Crane_2$ || … $Crane_M$), therefore, during the simulation process of the system when two or more overhead cranes are in series, if one crane fail, all the chain of cranes in series stop, overwise, when two or more cranes are in parallel, if one crane fail, the redundancy system is still working.

As a conclusion, we simulate independently the LC_i for each overhead crane i, then we combine all the N-series cranes in each M-parallel chain of cranes using the junction symbol &, and then we aggregate all the equivalent M-parallel chain of cranes using the junction symbol || to obtain the system loading capacity X. Below, we define the general notation for the overhead cranes system loading capacity:

$$X = \mathop{(||)}_{m=1}^{M} \mathop{(\&)}_{n=1}^{N} LC_{m,n} \tag{5}$$

2.3 Risk Indicator Modelling

The risk function denoted as R can be generated with the sum of $X + Y$ random, independent, and non-negative variables. By definition, the product of $R(s) = P(s)Q(s)$ is defined with the generating function $P(s) = \sum_{j=0}^{\infty} p_j s^j$ of X and the generating function $Q(s) = \sum_{j=0}^{\infty} q_j s^j$ of Y. Consequently, the generating function of $R(s)$ is generally defined by the convolution formula:

$$r_k = \sum_{j=1}^{k} p_j q_{k-j} \tag{6}$$

where p_j and q_j are the generated sequence from $P(s)$ and $Q(s)$ respectively.

In this investigation, X is the overhead cranes system loading capacity distribution function affected by the maintenance scheduling defined in (5), and Y

is the production line capacity defined in (2). The risk function is denoted in this investigation as R and is defined below as a convolution product between (5) and (2):

$$R = \begin{cases} \sum_{t=1}^{T} Y_t - X_t & \text{if} \quad X_t < Y_t \\ 0 & \text{if} \quad X_t \geq Y_t \end{cases} \tag{7}$$

where $t = 1, 2, 3, \ldots, T$ (*Simulation Window*).

The expected value of the risk function $E[R]$ is defined in this paper as *Capacity Loss*. In this work, to estimate $E[R]$ the Monte Carlo simulation method is used. The convergence process is fluctuating in this method. However, the error level decreases when the number of samples increases, according to the law of large numbers. In this method it is not practical to run a simulation with many samples, because more calculation time is required. Therefore, it is necessary to balance the required precision and the calculation time with a stop criterion. This criterion guarantees that the simulation continues, until the risk indicator has the precision specified for the simulation. The parameter used as stopping criterion in the method is the coefficient of variation β defined below.

$$Capacity\ Loss = E[R] \pm \beta E[R] = E[R] \pm \frac{\sigma[R]}{E[R] \cdot \sqrt{N}} E[R] = E[R] \pm \frac{\sigma[R]}{\sqrt{N}} \tag{8}$$

3 IME-PLATFORM: MATHEMATICAL PARAMETERIZING

The system analyzed have 33 overhead cranes with loading capacity between 2-80. Depending on operation time and loading capacity, each crane has weekly, every two weeks or monthly inspection frequency as we describe in the Table 1.

Table 1: Inspection frequency relation.

Capacity (tons)	Inspection frequency	*TTM* (hours)	*TDM* (hours)
50T – 120T	Weekly	168	3
32/8T – 20T	Every 2 weeks	336	3
5T-8T	Monthly	672	3

The inspection frequency are maintenance tasks, therefore in the model are considered as $TTM_{i,k}$ and $TDM_{i,k}$,, where k-th is the number of inspections for each overhead crane depending on the simulation window. In the historical degradation data case, the fitted distribution function for each crane is a result of the fitting-selection decision making flow diagram from previous work.

In order to parameterize the degradation process of the system, the Table 2 summarize all the finals distributions selected for each overhead crane.

Table 2: Degradation distribution parameters.

Crane ID	Failure time distribution	Repair time distribution
807	Exponential $\mu = 743.80$	Lognormal $\mu = 1.07$; $\sigma = 0.93$
808	Weibull $a = 1796.93$; $b = 0.60$	Generalized Pareto $k = -1.05$; $\sigma = 12.56$; $\theta = 0$
809	Gamma $a = 0.54$; $b = 2607.04$	Inverse Gaussian $\mu = 6.82$; $\lambda = 4.70$
810	Exponential $\mu = 9184$	Exponential $\mu = 3.25$
870	Birnbaum Saunders $\beta = 377.02$; $\gamma = 2.59$	Loglogistic $\mu = 0.98$; $\sigma = 0.48$
871	Weibull $b = 0.64$; $a = 1060.19$	Inverse Gaussian $\mu = 2.30$; $\lambda = 4.43$
1011	Exponential $\mu = 3254.86$	Exponential $\mu = 8.60$
1010	Inverse Gaussian $\mu = 476.41$; $\lambda = 79.40$	Inverse Gaussian $\mu = 5.9$; $\lambda = 1.87$
872	Exponential $\mu = 2396$	Exponential $\mu = 6.63$
873	Exponential $\mu = 5571.4$	Exponential $\mu = 4.53$
874	Exponential $\mu = 1189.2$	Exponential $\mu = 72.5$
879	*NaN*	*NaN*
1001	Weibull $b = 0.82$; $a = 458.66$	Lognormal $\mu = 1.44$; $\sigma = 1.14$
1000	Burr $\alpha = 2318.3$; $c = 0.75$; $k = 3.15$	Inverse Gaussian $\mu = 10.44$; $\lambda = 4.59$
1002	Exponential $\mu = 3285.9$	Exponential $\mu = 12.95$
1003	*NaN*	*NaN*
1004	*NaN*	*NaN*
1005	Weibull $b = 0.70$; $a = 429.64$	Inverse Gaussian $\mu = 65.65$; $\lambda = 2.93$
1006	Exponential $\mu = 2534.4$	Exponential $\mu = 5.07$
1007	Exponential $\mu = 1125.7$	Exponential $\mu = 2.6$
1008	*NaN*	*NaN*
1009	*NaN*	*NaN*
1016	*NaN*	*NaN*
1021	*NaN*	*NaN*
502	Exponential $\mu = 1478.2$	Exponential $\mu = 4.38$
981	Birnbaum Saunders $\beta = 508.68$; $\gamma = 3.13$	Inverse Gaussian $\mu = 16.82$; $\lambda = 2.11$
983	Weibull $b = 0.62$; $a = 611.51$	Inverse Gaussian $\mu = 8.52$; $\lambda = 3.53$

Table 2: Degradation distribution parameters (cont.).

Crane ID	**Failure time distribution**	**Repair time distribution**
985	Generalized Extreme Value k = 0.8; σ = 1176.1; μ = 903.95	Inverse Gaussian μ = 72.79; λ = 2.69
804	Exponential μ = 4008.8	Exponential μ = 3.59
813	Burr α = 1027.3; c = 0.78; k = 2.92	Inverse Gaussian μ = 22.66; λ = 2.73
815	Nakagami μ = 0.28; Ω = 2852.2	Inverse Gaussian μ = 3.88; λ = 2.03
812	Exponential μ = 8564.6	Exponential μ = 6.44
811	Exponential μ = 8803.5	Exponential μ = 4.18

Note: *NaN* means non failures registered.

Once we know all the parameters related with the overhead cranes system capacity, the next step is the production line capacity. Two essentialise information, the monthly *STD* is 12; 10; 16 and 12 hours every week respectively, therefore *STB* between them are 168 hours; and the efficiency indicator is 85% in the simulated scenario.

In the case of the simulation parameters, the simulation window is one year (8760 hours) and we assume robust expected value estimation (*Capacity Loss* indicator) by Monte Carlo simulation when ε = 0.01.

4 IME-PLATFORM: MATHEMATICAL SOLVING

The model is fully implemented in MATLAB (R2019b), a multi-paradigm numerical computing environment and proprietary programming language developed by MathWorks and can be running in any personal computer.

As we describe above, the model has a stochastic non-linear objective function with bounded constraints. In order to solve this specific problem, PSO algorithmic was used because *Capacity Loss* risk indicator (objective function value given the maintenance scheduling) is the results of a convolution by Monte Carlo simulation, therefore we do not know the objective function derivate and Newton's, Lagrange, quasi-Newton or Sequential Quadratic Programming traditional methods cannot be used.

Knowing the features of the objective function, during the model implementation three possible well-stablished algorithms to solve derivative free problems were found and tested: GA (genetic algorithm), PSO (particle swarm optimization), and Nelder-Mead modified (NMm).

GA as a global searching algorithm, in large search regions needs numerous evaluations in the objective function to find the minimum.

NM, by definition is a searching algorithm without restriction, but during the implementation was possible bound the independent variables of the objective function to adapt the algorithm to the problem (NMm). NM has a limitation related with the number of independent variables. Independently of the objective function, when the number of independent variables is more than ten, the algorithm rarely finds the global optimum if the initialization of the search is not accurate.

Given the previous statements, PSO a local searching algorithm, is the option selected to be used because behaves better in this particular problem, finds the solution with less evaluations in the objective function, and as a consequence, the time needed to solve the problem is lower than GA. In addition, the number of independent variables is not a limitation for this algorithm.

PSO is fully applicable to this problem. PSO algorithmic used in this investigation is based on the algorithm described in (Kennedy et al., 1995), using modifications suggested in (Mezura-Montes et al., 2011) and in (Pedersen, 2010). PSO algorithm iterates until it reaches a stopping criterion, in this case, when the relative change in the best objective function value is less than 1.0000e-06 (Function Tolerance described in the diagram flow).

Once the optimization algorithm used on the solution and the full parameterization are described, the results of the proposed optimization model given the steel plant scenario is shown in Figure 3.

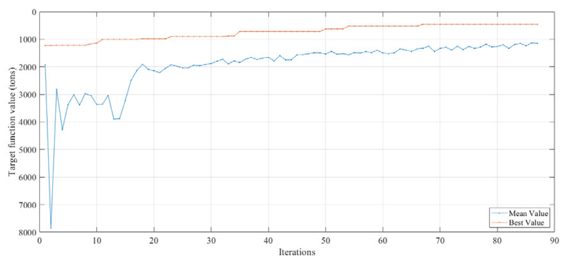

Figure 3: Convergence process of the optimization algorithm.

Figure 3 is the convergence process of the optimization algorithm and shows how the *Capacity Loss* decrease when the maintenance scheduling change. Proper planned maintenance scheduling process improve the operational efficiency in the steel plant, and the CLCS guaranty the expected results. The exploitation efficiency system based on risk management is valuable for the entity manager because he/she can decide according to standards risk level, what would be the best moment in the year to perform the maintenance process in the system.

Simulation-based approaches are powerful for modeling stochastic processes with complex functions, but the time to simulate these processes can be a limitation with the current computing power. In our case the average time duration of ten consecutive simulations performed with an i5 5250U 1.6 GHz CPU for the described parametrization is $[(1.955813 \pm 0.072131) \cdot Ns \cdot E]$ seconds.

5 CONCLUSIONS

The paper describes with a parameterized scenario, how the exploitation efficiency system based on risk assessment find the optimal overhead cranes maintenance scheduling in the steel plant. Experimental results show that presented closed-loop control model can help to organize the maintenance scheduling strategy in the steel plant. The paper solves the assessing risks problem of transportation process in the steel plant through the simulation-based approach which considers the relationship between random factors (historical degradation data fitted by machine learning framework) during the production process and maintenance scheduling process (planned process, making-decision framework).

The presented model has the advantage of minimum set of data needed for robust decision making, but two fissures are in place, the model is a local focused problem solution (unique), means, we do not have any comparative reference to assess the model, just validations by steps and study cases, and the time because we use simulation-based approach.

The local solution is well accepted by the steel plant and futures steps of the investigation will recover the results of the application in practice, but still remain open the generalization of the proposal in others system with similar orientation problems.

The presented model opens the way to extensive simulations under various scenarios and conditions, with the possibility to be updated in real-time, to detect anomalies, to control systems and to conduct accurate diagnostics and prognostics of cranes into selected scenarios.

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