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Resource Leveling Optimization in Construction Projects of High Voltage Substations Using Nature-Inspired Intelligent Evolutionary Algorithms

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***Abstract*—**High Voltage Substations (HVS) are the intermediate step between production of power and successfully transmitting it to clients, making them one of the most important checkpoints in power grids. Nowadays - renewable resources and consequently distributed generation are growing fast, the construction of HVS is of high importance both in terms of quality and time completion so that new energy producers can quickly and safely intergrade in power grids. The resources needed, such as machines and workers, should be carefully allocated so that the construction of a HVS is completed on time, with the lowest possible cost (e.g. not spending additional cost that were not taken into consideration, because of project delays), but in the highest quality. In addition, there are milestones and several checkpoints to be precisely achieved during construction to ensure the cost and timeline control and to ensure that the percentage of governmental funding will be granted. The management of such a demanding project is a NP-hard problem that consists of prerequisite constraints and resource limits for each task of the project. In this work, a hybrid meta-heuristic method is implemented to solve this problem. Meta-heuristics have been proven to be quite useful when dealing with high-dimensional constraint optimization problems. Hybridization of them results in boost of their performance.

***Keywords*—**High voltage substations, nature-inspired algorithms, project management, meta-heuristics.

I. Introduction

A very important task in project management is the need to properly allocate resources, so that the total cost of the project is the lowest possible. The proper allocation of resources in construction has been a challenging problem in literature [1], [2].

One of the most important parts of a power grid is the existence of HVS, which transmit the power that is produced from generating units to the network. The construction of a HVS is a demanding project that lasts approximately two years and requires a lot of resources, mainly excavators and workers.

Intelligent techniques have been proven to be quite successful in multiple occasions, where resource leveling is done in real projects. Applied in small [3]-[6], medium [7], [8] or large [9], [10] and very large projects [11], nature inspired techniques proved to be superior compared with other methods. In this work, Sonar Inspired Optimization (SIO) is used to find the optimal resource profile in a real project, i.e. the construction of a HVS. SIO has been successfully applied on multiple engineering problems [12], one of them being the resource leveling [13].

Being the first method to cope with the construction of a HVS, SIO's results are compared with the corresponding results of the resource profiles that Early Start and Late Start methods would give. Different objective functions that reflect the possible optimization goals of the decision maker are implemented. What is more, trying to boost the performance of SIO, a hybrid scheme consisting of SIO and Simulated Annealing (SA) is implemented. The addition of SA will provide a higher exploration at the beginning of the algorithm and higher exploitation while the iterations proceed. Both SIO and SIO-SA are superior to Early and Late Start methods.

II. Resource Leveling in Project Management

A. In General

In resource leveling, the main goal is the proper allocation of resources in such way that a criterion is met. Such criteria could be (a) the minimization of maximum daily resources, (b) the least possible deviation of daily resources from the average resources per day and (c) the maintenance of daily resources in approximately the same amount of resources as the day before.

Each criterion expresses different goals. For example, the minimization of maximum daily resources can be handful when a maximum amount of cost per day must be met, while the minimum deviation of daily resources from the average resources per day would be useful for companies that would like to employ approximately the same amount of people each day.

As stated in [14], other objectives than these described below for this kind of problem are the minimization of distribution of resources (R^2), the minimization of standard deviation of resource allocation (StD), the minimization of the ratio between the multiplication of project's duration with the square of daily usage of resources and the square of the sum of all of the project's resources (RIC), $STEP$ criterion which aims to minimize the uniform resource use from period to period and Entropy of Resources. Each one of the objectives mentioned in this section can be used for the Resource Leveling problem individually or cooperatively with any of

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the rest.

B. Minimization of Maximum Resource Usage

This objective aims in the minimization of the maximum resources needed in a unit of time in a project [15]:

$$G_f = \max\{F(t), t = 1,2,..,T\} \tag{1}$$

where $F(t)$ is the amount of resources used at the time t. It can be calculated by adding the resources r_i needed for every task i which is active at the time:

$$F(t) = \sum_{i\in\{1,..,n\}} r_i(t) \tag{2}$$

with the limitation that the total duration of the project is not greater than the minimum time calculated by the Critical Path Method (CPM) and also, that every task begins when all the prerequisites are completed.

C. Minimization of Mean Resource Usage

The difference between actual and desirable resource usage is measured in this objective, so that the resources which are way above average usage are minimized [16], [17]:

$$RLI = \sum_{t\in\{1,2,..,T\}} \left|\left(\sum_{i\in\{1,2,..n\}} r_i(t)\right) - \left(\frac{\sum_{i\in\{1,2,..n\}} r_i d_i}{T}\right)\right| \tag{3}$$

D. Resource Profile Evaluation in This Work

Based on the criteria mentioned in the beginning of this section, different evaluation functions are used. Specifically:

a) for the minimization of maximum daily resources, G_f, R^2 and RIC are preferred
b) for the least possible deviation of daily resources from the average resources per day, RLI and StD are commonly used
c) for the maintenance of daily resources in approximately the same amount of resources as the day before, $STEP$ and Entropy of Resources are used.

The project in this study is a construction project; therefore, the minimization of maximum daily resources would be a reasonable assumption, due to the fact that the concessionaire would like to keep daily costs as low as possible. However, in this work the profiles given from RLI criterion are also studied to highlight the difference of the best strategy based on different objectives.

III. HVS Construction

The implementation of the 2010/75/EU Directive provided a boost to the already uprising Distributed Energy Resources (DER). Most conventional power stations are planned to be shut down in favor of less Industrial Emissions Energy Production. Consequently, the existing centralized production (few large coal-fired power plants located away from consumers) shrinks and it is being replaced by a great number of smaller scale power stations distributed near the grid and the consumption. In this context, there is an increasing need for the construction of new HVS in order to connect the production to the grid. Through the HVS, the Voltage Level supplied by the producer (20 or 30 kV) transforms to Transmission Grid Voltage (150 kV). In order to eliminate losses, the HVS shall be constructed close to the production location. When it comes to wind power, the energy is generated by wind parks usually developed in high altitude locations, where the wind potential is great and the HVS shall also be constructed within a short distance from the wind parks. Thus, during the construction of an HVS, the resources profile used shall be optimized in order to eliminate transportations of equipment and staff. In this context, there is an increasing need for the construction of new HVS in order to connect the production to the grid.

TABLE I
Data of the Project of HVS Construction

Task ID	Duration	Resources	Prerequisites
1	0 days	0	-
2	270 days	12	1
3	60 days	6	2
4	60 days	4	3FS-30 days
5	270 days	9	4
6	14 days	6	5FS-30 days
7	450 days	16	6
8	420 days	13	7FS-30 days
9	660 days	3	6
10	660 days	6	6
11	60 days	4	10FS-10 days
12	20 days	8	5
13	120 days	9	5
14	270 days	8	6FS+90 days
15	240 days	12	7
16	20 days	11	14
17	90 days	8	15
18	480 days	15	5
19	90 days	8	8
20	20 days	8	19
21	15 days	1	15
22	20 days	1	14FS+30
23	15 days	1	15FS+30
24	5 days	1	16
25	10 days	1	17
26	5 days	15	18
27	10 days	11	17
28	210 days	3	8FS-60 days
29	90 days	2	8FS-60 days
30	180 days	2	23
31	105 days	6	24
32	105 days	8	27
33	75 days	14	22
34	75 days	2	26
35	75 days	11	25
36	60 days	5	11
37	270 days	14	8FS-30 days
38	105 days	4	37
39	75 days	6	38
40	0 days	0	39

This paper deals with the Resource Leveling Optimization (RLO) of a real project of a HVS Construction. The construction process of the HVS consists of 40 different tasks as presented in Table I. The notation FS denotes the relation finish-to-start of the current task with its prerequisite. In related literature, optimization is commonly achieved for small scale artificial projects using Genetic Algorithms and evaluated through seven different resource profile evaluation functions [14] in comparison to the Early Start (ES) and Late Start (LS) Resource Profiles.

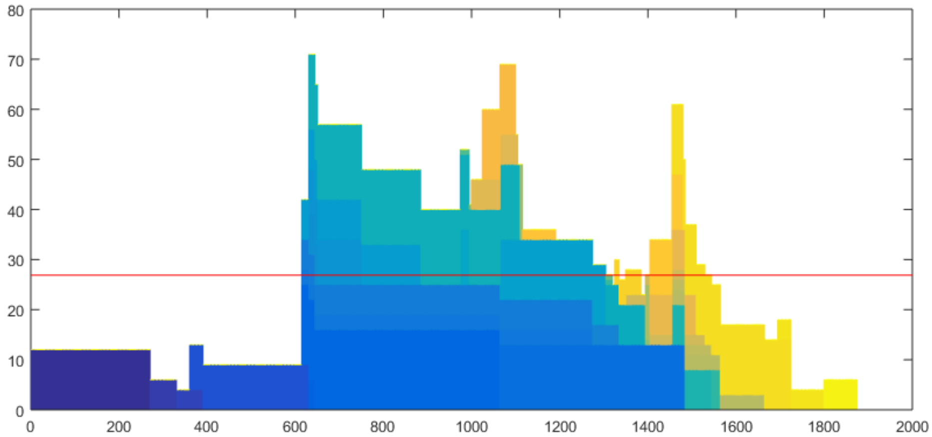

Fig. 1 Resources Profile of Early Start (ES) solution

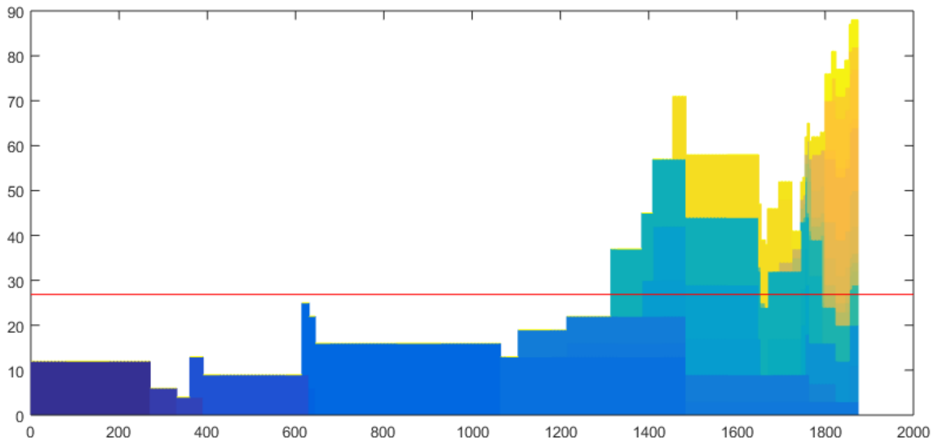

Fig. 2 Resources Profile of Late Start (LS) solution

IV. Optimization Methods

A. SIO

Recently, SIO has been used successfully to tackle resource leveling problem of artificial projects [13]. The main difference between this method and any other intelligent meta-heuristic is the fact that each agent performs a local search around itself, in each iteration of the algorithmic process.

SIO has been proposed by [18] as an intelligent nature-inspired optimization technique. The process is briefly presented in Algorithm 1. The most important features in this algorithm are the parameters of intensity and effective radius, which increase and decrease based on the quality of the solution.

Each agent starts with an initial effective radius which determines the maximum distance of the first step that the agent can perform in each dimension of the solution space. During the algorithmic process, the intensity of each solution (showing the quality of the solution in opposition with the previous position of the current agent) increases when a better solution is found and decreases otherwise. Due to the inverse relation between intensity and radius in nature, which is used in SIO too, the effective radius of a better solution is decreasing and a local search around this solution is performed by the agent. On the other hand, if the agent is exploring a worse solution, the effective radius is increasing to let the agent make bigger jumps in the solution space.

At start, the position of agents is initialized randomly somewhere in the solution space. The next steps are repeated until the stopping criteria are met. In the experiments conducted, the stopping criterion is the maximum number of iterations.

Algorithm 1: SIO for Resource Leveling

Initialization of population and algorithm's parameters
while stopping criteria not met
    Relocate agents without improvement for some steps
    Update effective radius for every agent
    while full_scan = false
        Update the rotation angle in every dimension
        Calculate fitness of possible position

Save the best so far for each agent in the current scan
End
Correct any agent that has exceeded solution space
Update intensity of each dimension for every agent
Update best position and fitness
End

In the beginning of each iteration of the algorithm, agents with no improvement for some steps change position to search another area of the solution space. The maximum number of iterations without improvement is defined at the beginning of the algorithm as described in [13]. Then, another mechanism that models the concept of SONAR is implemented, named Full Scan Loop. Various possible solutions around each agent (i.e. the candidate solutions) are generated. These solutions are limited by the effective radius which defines how big would be the steps of the agent in every dimension of the problem. Because of the rotation around each dimension's position, which resembles the rotation of the beam of SONAR, this process is referred as Full Scan Loop and is repeated until one of the angles mentioned in [13] bypasses 360°. For each agent the best solution found during the Full Scan Loop is saved.

B. SIO for Resource Leveling

Each agent is considered to be a solution:

$$X_i = \{st_i^1, st_i^2, st_i^3, \dots, st_i^n\} \tag{4}$$

where st_i^j is the starting time of the j-th task for the i-th agent, $i \in 1,2,\dots,N$ and N being the maximum number of agents, while n is the maximum number of tasks of the project. The calculation of Early and Late Start of each task is needed to set them as the lower and upper bound of each dimension of the problem, so that:

$$upper\_bound^j = ES^j \tag{5}$$

$$lower\_bound^j = LS^j \tag{6}$$

Each dimension j refers to the corresponding task ID of the project. Setting these bounds, the tasks composing the Critical Path cannot take any other value than the starting time which is defined by the early and late start. The usage of the bounds ensures that the algorithm does not produce non-feasible solutions and thus, computational time and power are saved. Therefore, each solution is generated using the equation:

$$st_i^j = lower\_bound^j + (upper\_bound^j - lower\_bound^j) \cdot rand \tag{7}$$

where the starting time st_i^j for the j-th task of the i-th solution (agent) takes a random value between the lower bound, i.e. early start, of the j-th task and the corresponding upper bound, i.e. late start, of the same task.

C. Relocation of Agents

When a solution has not been improved for a predefined number of steps, the current agent is relocated in the solution space. To avoid premature convergence, if the quality (in terms of objective function) of the agent is greater than the average quality of the population the new position of the current, agent i is calculated as in (7). Otherwise, the best solution found-so-far is used as a reference point and the agent is relocated near it:

$$st_i^j = st_{best}^j + r_{0\,best}^{\,j} \cdot rand \tag{8}$$

where st_i^j is the position of i-th agent in the j-th dimension, st_{best}^j is the value of the best-so-far solution for the j-th dimension, $r_{0\,best}^{\,j}$ is the effective radius of the best-so-far solution in the j-th dimension and $rand$ is a random uniformly distributed number.

D. Feasibility of Solutions

A major problem when dealing with constrained problems such as Resource Leveling is how to generate only feasible solutions. Computational time and power are two significant factors for Decision Engineering problems. However, for tasks that have prerequisites, (7) does not provide a feasible solution. In that case, the earliest start of the task is limited by its prerequisites' ending time. The prerequisite task that ends last sets the new lower bound of the current task and (7) is redefined as:

$$st_i^j = temporary\_lower\_bound^j + (upper\_bound^j - lower\_bound^j) \cdot rand \tag{9}$$

where $temporary\_lower\_bound_j$ is calculated as the maximum value of the addition of starting time and duration of each prerequisite task with the finish-to-start relation of the j-th task with any previous task, as:

$$temporary\_lower\_bound_j = \max\ \{st_k^j + duration_k + FS_k^j, k \in (Prerequisites)\} \tag{10}$$

where $duration^k$ is the known duration of the k-th task, st_k^j is the starting time of each k task that is a prerequisite for the current task j and FS_k^j denotes the finish-to-start relation of the j-th task with each prerequisite task k, as it can be seen in Table I.

Equations (9) and (10) are used when generating a new solution, either in initialization phase or in the relocation phase. The correction mechanism described before, when needed, reforms (9) as:

$$st_j^i = temporary\_lower\_bound^j + (upper\_bound^j - lower\_bound^j) \cdot \cos(st_j^i) \tag{11}$$

to fulfill the relation:

$$lower\_bound^j \le st_i^j \le upper\_bound^j \tag{12}$$

E. SIO with SA Operator

In order to increase the diversification of solutions, the rejection mechanism of SA [19] is used in the relocation section of SIO.

SA is considered a well-known established technique with multiple applications. A characteristic mechanism of SA is the Metropolis Criterion used to accept worse solutions with a probability p so that diversification of solutions is achieved. This probability is calculated as:

$$p = e^{-\frac{q_{best}-q_i}{T}} \tag{13}$$

where q_{best} denotes the quality (value of objective function) of the best solution, q_i is the quality of the current agent i and T is the parameter of temperature of SA, which is gradually decreasing through the algorithmic process.

In this study, this probability is used instead of the condition described above, where the quality of the current agent is compared with the average quality of the population to decide if the relocation would be done via (7) or (8).

V. Experimental Results

The data used in this work come from a real project and are presented in Table I. This work is the an attempt to perform resource leveling in that project. Therefore, the profiles of Early and Late Start were used as benchmarks. Fig. 1 and 2 show these profiles, where the red line denotes the average resource usage of the profile. The evaluation of these two profiles for each objective is shown in Fig. 5 and 6.

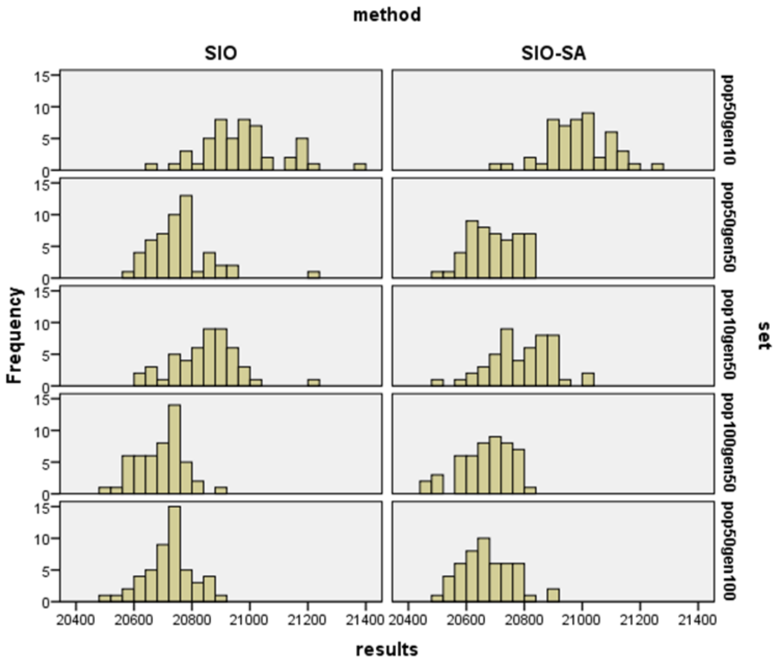

Fig. 3 Comparative histograms of different experimental sets of each optimization method in RLI

To investigate the performance of the algorithm, parameter tuning has been done. All experiments were done using MATLAB R2015a on a 4GB, 3.6GHz Intel Core i7-4790 Windows 10 Pro and on a 16GB, 3.6GHz Intel Core i7-9700KF Windows 10 Pro. Five different pairs of population and generations were selected. At start, the population was set to 50 agents and different values of generations were selected, i.e. 10, 50 and 100. Then, this process has been done in reverse, where the number of generations was set to 50 and the remaining values of 10 and 100 agents were selected. In Tables III and IV, the results for different parameter values in both SIO and SIO-SA schemes are shown. In the parenthesis, population size and number of generations are denoted, e.g. (50-10) means that SIO was tested with 50 agents and 10 iterations. To measure the statistical performance of each pair of parameter values, 50 independent runs were conducted in each case. All other parameters were kept unchanged during the experimental process and they are presented in Table II.

TABLE II
Parameter Values of Optimization Methods

	SIO	SIO-SA
checkpoint/scans	0,08	0,08
T (temperature)	-	1000
decrease rate of Temperature	-	0,95

As it can be seen in Tables III and IV, both SIO and hybrid scheme of SIO and SA were superior to Early and Late Start methods. As expected, both methods performed better for a larger number of population and generations.

To depict the difference of the solution given by each criterion, and thus by different objectives, in Fig. 4 the resource profiles of the best solution given by each method for both criterions is compared with the corresponding profiles of

ES and LS methods.

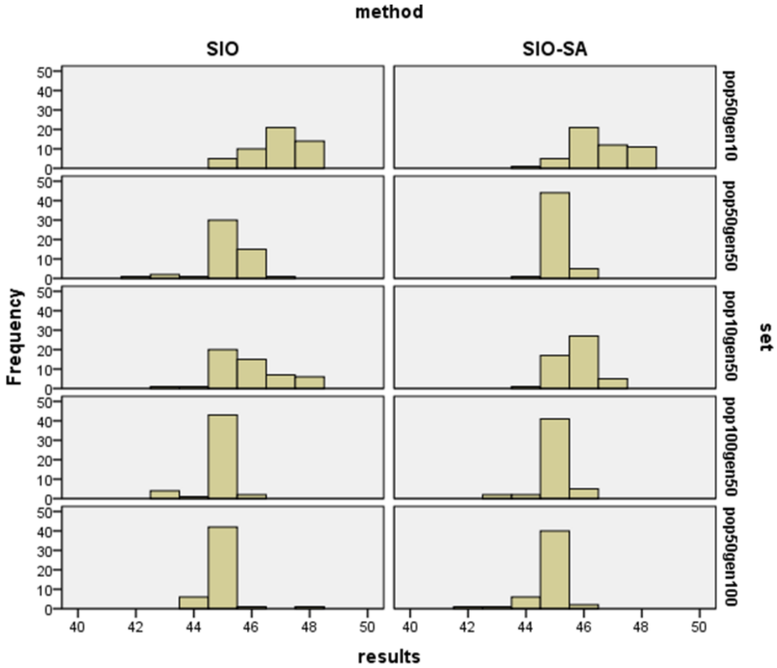

Fig. 4 Comparative histograms of different experimental sets of each optimization method in G_f

TABLE III
COMPARATIVE RESULTS FOR RLI CRITERION

	bestRLI	meanRLI	stdRLI
ES	30795	-	-
LS	33689	-	-
SIO (10-50)	20613	20848,68	110,616
SIO (50-10)	20671	20972,60	138,341
SIO (50-50)	20578	20749,02	80,9468
SIO (50-100)	20483	20722,48	82,3938
SIO (100-50)	20491	20690,76	79,0816
SIO-SA (10-50)	20515	20788,38	104,813
SIO-SA (50-10)	20708	20986,40	106,413
SIO-SA (50-50)	20517	20694,38	82,8128
SIO-SA (50-100)	20496	20673,12	91,8252
SIO-SA (100-50)	20453	20667,82	89,4805

TABLE IV
COMPARATIVE RESULTS FOR G_f CRITERION

	bestG_f	meanG_f	stdG_f
ES	71	-	-
LS	88	-	-
SIO (10-50)	43	45,88	1,1250
SIO (50-10)	45	46,88	0,9304
SIO (50-50)	42	45,18	0,8412
SIO (50-100)	44	44,96	0,5643
SIO (100-50)	43	44,86	0,6003
SIO-SA (10-50)	44	45,72	0,6645
SIO-SA (50-10)	44	46,54	1,0042
SIO-SA (50-50)	44	45,08	0,3371
SIO-SA (50-100)	42	44,82	0,6226
SIO-SA (100-50)	43	44,98	0,5474

Best RLI has been achieved by SIO-SA running with 100 agents for 50 generations. Best G_f has been achieved by both methods (SIO and SIO-SA), when SIO was running with 50 agents for 50 generations and SIO-SA was running with 50 agents for 100 generations. However, hybrid scheme of SIO-SA seems more robust in its performance, as it can be seen in Figs. 3 and 4.

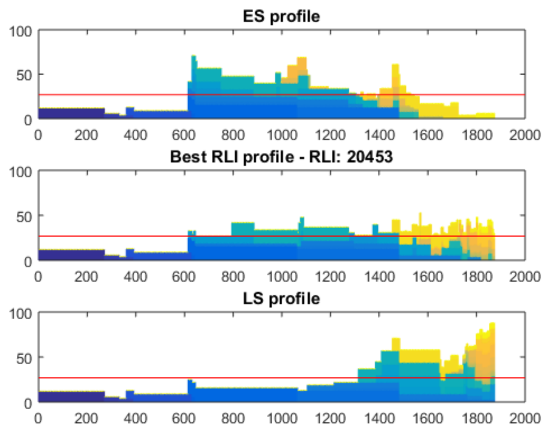

Fig. 5 Comparison of best resource profile based on RLI with Early and Late Start

VI. CONCLUSION

Resource Leveling is a demanding problem, which can be rather difficult when the number of tasks of the project, i.e. dimensions of the decision problem, is high enough. This study is focusing on leveling the resources of a real world project, which is the construction of HVS. Resource Leveling is performed by a nature-inspired intelligent algorithm, named

SIO, while also a hybrid method containing SIO and SA is implemented. Furthermore, this project has a lot of tasks that have a finish-to-start relation with their prerequisites. In literature there are not many works dealing with this kind of problems. SIO's correction mechanism ensures that only feasible solutions are checked throughout the algorithmic process. As a result, computational power and computational time are not wasted in non-feasible solutions.

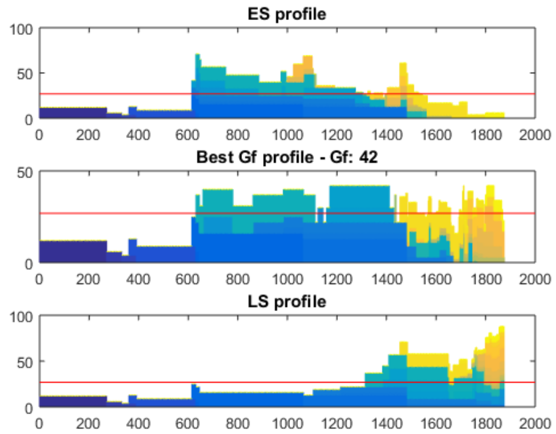

Fig. 6 Comparison of best resource profile based on G_f with Early and Late Start

Results show that both single and hybrid techniques manage to be superior to the ES and LS solutions. SIO was the one finding the best solutions, but the hybrid scheme of SIO-SA has slightly better solutions. What is more, SIO-SA is more robust than SIO.

This work is the first time that the aforementioned project is used. Therefore, the best profiles found based on each criterion may not be the optimal solutions of this problem. Thus, in future work, ways to improve the performance of the optimization methods will be investigated.

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