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# OCP optimizes its supply chain for Africa

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**Abstract :** Operations research specialists at the OCP Group, the Mohammed VI Polytechnic University, and the Polytechnique Montreal operationalized a system optimizing OCP's supply chain downstream activities. The system simultaneously schedules production, inventory, and vessels while ensuring the highest demand fulfillment. Therefore, it has become central to the OCP planning process, fundamentally transforming the supply chain and operations management within the group. Planners now use the optimizer's solutions and insights to improve plans. The system was initially a bottleneck curbing the use of other supply chain management tools. However, after its operationalization, OCP management credits the system with providing operational benefits, contributing to over a $240 million increase in annual turnover.

**Keywords :** Large-scale optimization, MILP solvers, metaheuristics, Benders decomposition, supply chain management

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By 2100, the world's population is expected to reach around 10.9 billion (Desa, 2019). With such growth, governments and international organizations need to ensure that there is a stable food supply for all people. Unfortunately, the world is facing an unprecedented food deficit due to rising prices that have been occurring well before the onset of the Ukraine war and a fertilizer crisis that has been negatively impacting previous food production seasons. Indeed, half of the world's food production is made possible by the use of mineral fertilizers (Van Kauwenbergh 2010, Cooper et al. 2011), and it is, therefore, essential to have sufficient quantities of fertilizers. The rising prices in developing countries have forced them to increase capacity in agriculture more than before using fertilizers (Khan et al., 2007). This is particularly true in Africa, where the population will more than double in this century (Desa, 2019). Here, where the shortage is the most obvious and where the most devastating food-threatening events arise, fertilizers are the main part of the equation to increase the food supply (Cordell et al., 2009).

Located in northwestern Africa (Figure 1), Morocco is a developing country ranked fifth among the 54 African countries in terms of nominal gross domestic product (GDP) in 2022 but remains very far behind OECD (Organization for Economic Co-operation and Development) countries with a world ranking of 61 among 190 countries. However, Morocco holds 70% of the world's phosphate rock reserves (Summaries, 2021), a crucial element for fertilizers' production, giving it a leading role in satisfying our planet's needs. Aware of its duty, the Moroccan government has been leveraging its expertise in agriculture and fertilizers production by establishing the largest agriculture hub in Africa. This hub is led by the OCP Group and the Mohammed VI Polytechnic University (UM6P). OCP Group is a Moroccan state-owned phosphate rock miner, phosphoric acid manufacturer, and fertilizer producer. Its vision is *to create sustainable growth for everyone*, and its mission is *to feed the soil to feed the world*. Founded in 1920, the company is one of the largest phosphate, fertilizer, chemical, and mineral industrial companies in terms of revenue worldwide. As for UM6P, it was founded in 2013 by the OCP Group charitable foundation and has since expanded to become a leading African research institution, contributing to research with international standards. It prioritizes research and innovation in industrialization, agriculture, food security, sustainable development, mining, and social sciences. The institute is oriented towards applied research and innovation and is engaged in economic and human development with a focus on African development. Given their prominence, the Moroccan government would like OCP Group and UM6P to act as national and African champions in order to serve as a locomotive for other African companies and universities. They are led by national and African researchers, and have collaborations and partnerships with several national and international universities and corporations (OCP 2022, UM6P 2022).

Recently, OCP Group has been focusing more and more on promoting *precision farming*, i.e., determining the right fertilizer for the right soil (Auernhammer, 2001). With the UM6P's support, the goal is to reduce the current imbalance in the African market by producing more precise fertilizers in sufficient quantities to remedy food shortages and withstand food shocks. However, the use of fertilizers in Africa is still restricted, highlighting that the continent is in huge need. For instance, only 30%-40% of Ethiopian smallholders use fertilizers, with only 37 to 40 kg per hectare, an amount substantially less than the recommended rate (Mekonnen and Kibret, 2021). In addition, many farmers are denied access to fertilizers because of the logistical difficulties of distributing imported fertilizer in a large, landlocked country with long distribution channels and lacking production, transportation, and storage infrastructure. These factors lead to high importation costs and long lead times for distribution. Therefore, the OCP's proximity is a great advantage even for east African countries like Ethiopia, which are relatively farther away than West African countries.

The African continent could potentially become a large market in the long term. It is full of considerable assets, including a high proportion of young people, the availability of quality cultivable land, the abundance of water resources, and the potential for industrial, environmental, social, and human development. As of today, Africa has more than 65% of the arable land available on the planet with a diversity of agro-ecological zones and climates, which creates vast potential in terms of the combination of agricultural products that can be grown and marketed to the whole world. Therefore, at the OCP, Africa is believed to be the center of solutions to global food security challenges. Still, it is not a luxury market, so there is pressure to reduce the price. Thus, while OCP makes donations and provides discounts to several African countries in need, it also seeks to meet margins by offering a correct price given the African context. To accomplish this, and since OCP Group covers, so far, 80% of fertilizer demand in Africa (OCP, 2022), the Moroccan leader is committed to minimizing costs and optimizing processes.

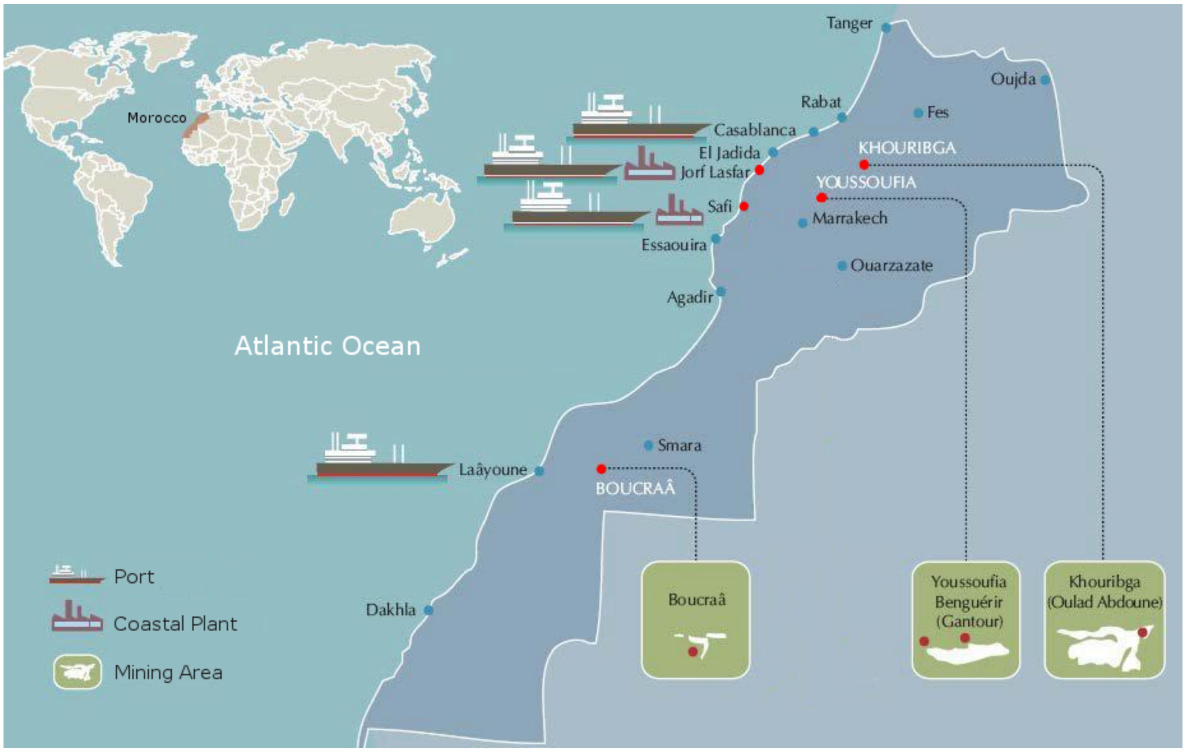



**Figure 1: Morocco location with OCP group sites in red dots.**

## Problem description

OCP Group has five main sites (Jorf, Khouribga, Safi, Boukraa, and Benguerir) represented by red dots in Figure 1. It specializes in phosphate mining, production, and exportation and its phosphate products include raw phosphate, phosphoric acid, and phosphate fertilizers. Each year, the Moroccan corporation produces, on average, 37.6 million metric tons of phosphate rock, accounting for 31% of the world market share. In 2021, the group's turnover reached $8.83 billion (OCP, 2022).

The main focal location of this research is the Jorf site (El Jadida, Morocco) in the red frame in Figure 2. It is the largest among the OCP's sites, and is where 90% of production happens. Before reaching the Jorf site, phosphate rocks are extracted from the mine. Trucks transport these rocks to the physical treatment facility, where they undergo the washing and floating processes. The obtained phosphate powder is transported for chemical treatment by a 187 km slurry pipeline to the Jorf site. In the coastal processing plant of this site, several derivative products are refined through 32 various chemical processes. The final products are stored in 29 large tanks before being supplied through conveyors to 6 quays where clients' vessels are loaded. The coastal processing factory and the loading port spread over an area of $5 \times 10^6$ $m^2$. The supply chain is connected through 102 conveyors and pipelines through which 45 raw, semi-finished, and finished products flow (OCP, 2022).

The number of finished products is high because each type of soil requires a specific fertilizer type in order to be environmentally-friendly. Thus, OCP Group's promotion of *precision farming* has increased

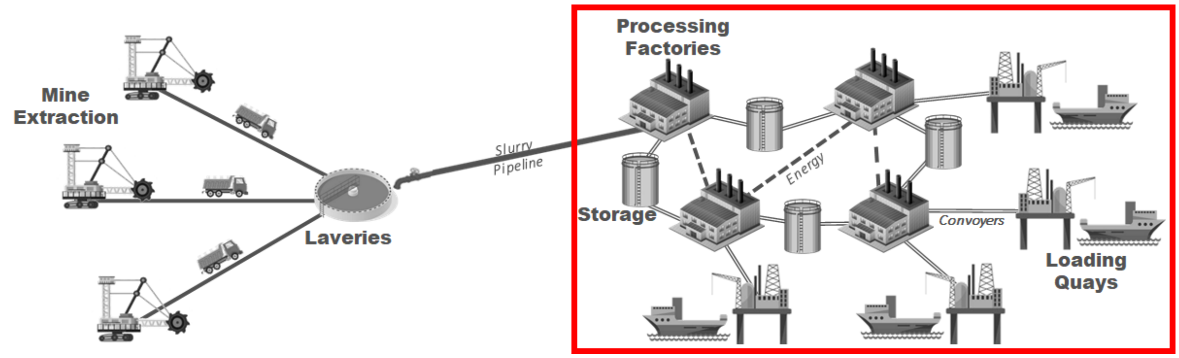



**Figure 2: From extraction to the Jorf site.**

the number of finished products from 3 initially to more than 30 as of today. It is expected that this number will exceed 75 shortly. However, the increased number of products offered by OCP has made the supply chain even more complex, generating large and complex scheduling problems. Given these problems' size, manual scheduling is untractable. Therefore, OCP Group has invested intensively in operations research (OR) tools to integrate and centralize downstream supply chain operations, i.e., production scheduling, inventory management, and vessel assignment (PSIMVA). Among these tools, the Downstream Logistics Planner (*DLP*) is the optimizer to tackle the PSIMVA problem. The latter is a huge combinatorial mixed integer linear programming (MILP) problem with complex multiobjective functions, millions of constraints, and hundreds of thousands of variables, tens of thousands of which are integers. For such a problem, no feasible solutions can be rapidly identified even using off-the-shelf optimizers. Further details are available in Er Raqabi et al. (2023b).

## Optimizer exploration prompts research effort

OCP Group had been relying on manual planning for many years. With the increasing number of products and supply chain complexity, the company acquired the *DLP* optimizer in 2014. However, *DLP* took more than 10 hours to generate feasible PSIMVA schedules, and therefore OCP continued to utilize manual planning. Towards the end of 2019, after remaining obsolete for many years, OCP decided to confirm the *DLP*'s potential with optimization experts from the Polytechnique Montreal (Poly) and UM6P.

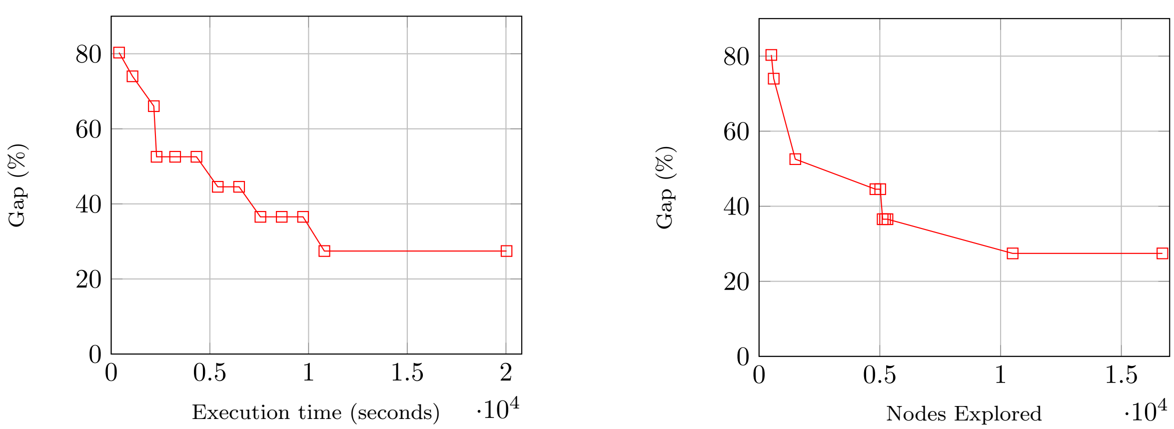
**DLP exploration obstacles.** When we, from Poly, started exploring the *DLP* with local researchers from UM6P, we faced several organizational and technical obstacles. On the organizational side, many OCP Planners preferred to rely on their expertise and manual scheduling, especially since they had witnessed the ineffectiveness of an obsolete *DLP* optimizer for more than five years. Within the company, there was doubt about the *DLP*'s usefulness. The mood and confidence were not great. Therefore, it was complicated to bring planners on board to support us in the exploration process. Furthermore, we had restricted access to the *DLP* optimizer for security reasons.

On the technical side, the limited access to the *DLP* optimizer led to several technical obstacles. First, at the beginning of the project, we only had access to PSIMVA instances (files with the ".lp" extension) generated by the optimizer. Second, we could not fully understand the data in these instances since we lacked business acumen. Third, we noticed many missing, redundant, useless, and hard-coded variables and constraints in the ".lp" files (e.g., vessel to load without assignment variables to quays).

To overcome these obstacles, we first organized meetings with reluctant stakeholders and highlighted that advanced optimization and operations research techniques will have a significant impact once implemented effectively. Advanced techniques can be time-consuming with the risk of losing users.

Therefore, to keep OCP end users adhered to the project we elaborated together a working strategy that was based on prototyping with a rapid cycle (for rapid feedback, i.e., to show them encouraging results). On the technical side, dealing with a black box and documentation that was not very detailed nor well-updated, we had to undergo reverse engineering to understand the up-to-date PSIMVA model implemented in the *DLP* optimizer. We rebuilt the PSIMVA model from the ".lp" files and the sparse documentation we had at hand by extracting variables, constraints, and objectives. The initial model assumes that we always solve optimally, which is not necessarily the case for such huge MILP problems. Furthermore, its objective function is a weighted sum of several key performance indicators (KPIs) where the weights are found by trial and error, and thus not mathematically founded. This implies that the objective function is neither significant nor interpretable and that the solver is likely to waste significant computational time exploring unpromising regions of the PSIMVA polyhedron. To resolve this issue, we remodeled the PSIMVA mathematically after discovering that the initial model was correct theoretically but not practically. Then, we created local databases to manage the PSIMVA models and understand the instances data. Rebuilding the model and creating local databases has allowed us to clean instances and ensure their consistency with the real world.

**Early exploration results.** After overcoming the aforementioned obstacles, we started exploring the PSIMVA models generated by the *DLP* optimizer. We first gave PSIMVA instances to CPLEX, the widely used commercial solver, to analyze further the MILP complexity. As shown in Figure 3, the default CPLEX fails to reach satisfactory schedules even after exploring more than 16,000 branch-and-bound nodes in more than 20,000 seconds, confirming that it consumes a large amount of time exploring unpromising regions of the polyhedron (Er Raqabi et al., 2023b). Before developing more sophisticated methods, we tried manually tuning CPLEX parameters to improve the solver performance. By configuring CPLEX parameters for each instance separately, we were able to improve performance and reach feasible schedules more rapidly (in less than 4 hours) compared to the 10 hours required by the *DLP*. These early exploration results confirmed the *DLP*'s potential, prompted the operationalization research effort, brought back confidence, and established the OCP-UM6P-Poly alliance.




**(a) Integrality gap evolution with execution time** **(b) Integrality gap evolution with the # of nodes explored**

**Figure 3: Default CPLEX performance on a PSIMVA instance.**

# Solution methodology

Given the PSIMVA's complexity and size, classical OR methods did not work efficiently. Thus, we opted for a gradual system improvement (Figure 4). The objective was to implement better solutions than the manual planning as soon as possible and to continue the improvement of the *DLP* optimizer step by step.

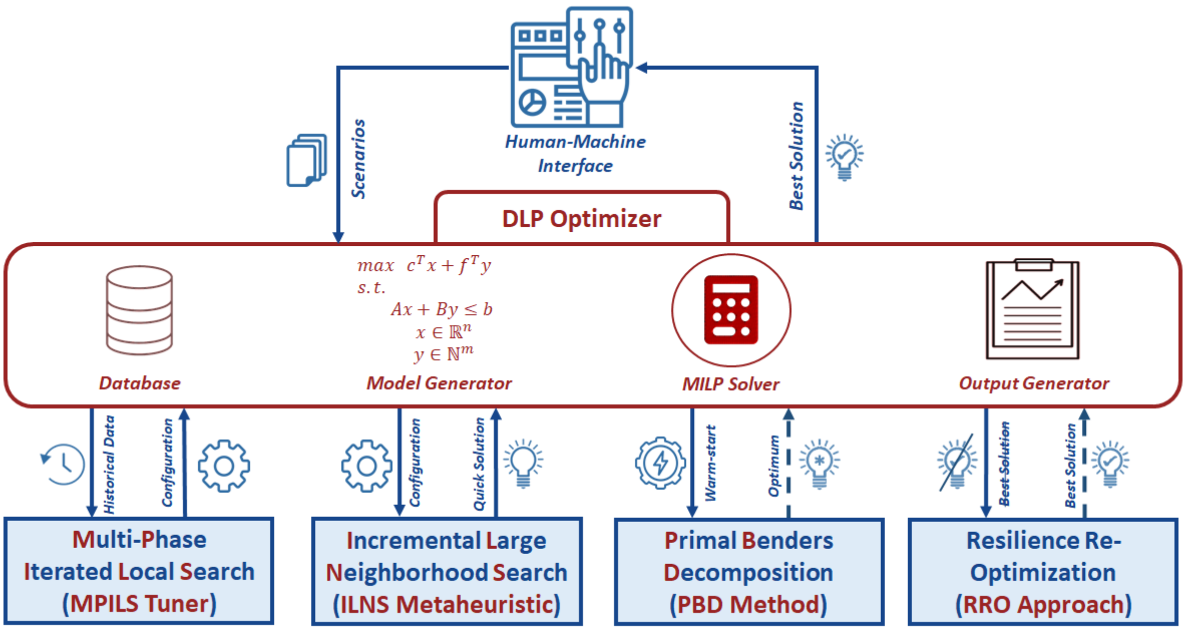



**Figure 4: Solution approach with the four steps: MPILS tuner, ILNS metaheuristic, PBD method, and RRO approach.**

The *DLP* optimizer incorporates a database, a model generator, a MILP solver, an output generator, and many other functionalities. OCP planners interact with *DLP* via a human-machine interface. Using this interface, they provide the optimizer with PSIMVA scenarios and obtain feasible schedules. Our role was to improve the *DLP* optimizer on two metrics: time and quality, i.e., reaching near-optimal, if not optimal, schedules as quickly as possible. Our solution approach involves four algorithmic solutions: the multi-phase iterated local search ($\mathcal{MPILS}$) tuner, the incremental large neighborhood search ($\mathcal{ILNS}$) metaheuristic, the primal benders decomposition ($\mathcal{PBD}$) method, and the resilience re-optimization ($\mathcal{RRO}$) framework.

## MPILS tuner

After noticing (during the *DLP* exploration) that manually configuring CPLEX parameters improves its performance on PSIMVA instances, we opted to configure the solver automatically. To do so, we used available state-of-the-art tuners such as irace (López-Ibáñez et al., 2016) and ParamILS (Hutter et al., 2009), neither of which worked efficiently because of the large number of possible configurations generated from CPLEX parameters and the PSIMVA complexity. In response to this, we designed the $\mathcal{MPILS}$ tuner, represented in the blue frame in Figure 5.

Instead of considering all parameters simultaneously, as in the literature, $\mathcal{MPILS}$ starts with an initial pool of parameters identified a priori using troubleshooting in the *Setup* step. The troubleshooting is based on OR expertise. Then, we tune the initial pool of parameters in the *Tuning* step. The latter consists of searching for satisfactory configuration(s) in a reduced search space induced by a small subset of parameters. After that, we use statistical learning techniques to remove potential deteriorating configurations in the *Learning* step and evaluation methods for parameters based on two metrics (optimality gap and time to optimality) to insert promising ones in the *Evaluation* step. The cycle continues until no parameter to tune is identified in the *Evaluation* step. Using the best configuration(s) returned by the automatic $\mathcal{MPILS}$ tuner, we could reach satisfactory solutions on the given instances from the Jorf site in an acceptable time. The $\mathcal{MPILS}$ schedules were good enough that OCP has decided to adopt them. Further details are available in Himmich et al. (2023).

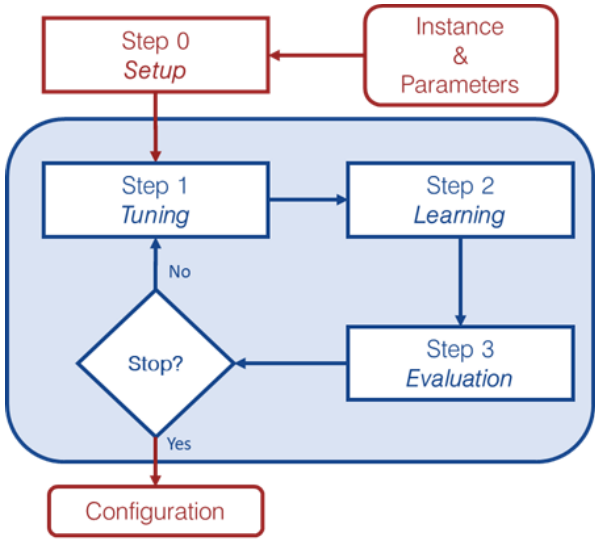



**Figure 5: $\mathcal{MPILS}$ tuner in the blue frame with three steps: Tuning step, Learning step, and Evaluation step.**

## ILNS metaheuristic

In the second phase of the project, we wanted to improve further the time and quality metrics based on model analysis, which highlighted that the PSIMVA instances become easier to solve when decomposing the scheduling time horizon instead of considering it as a whole. Thus, we designed the $\mathcal{ILNS}$ metaheuristic highlighted in the blue frame of Figure 6. It is a variant of the large neighborhood search (LNS) metaheuristic (Pisinger and Ropke, 2010). Given that solving PSIMVA directly with a MILP solver suffers from symmetry, we incorporated in $\mathcal{ILNS}$ a practical strategy to benefit from symmetry instead of breaking it. This strategy consists of a fixing mechanism that reduces the search space without affecting the PSIMVA solution.

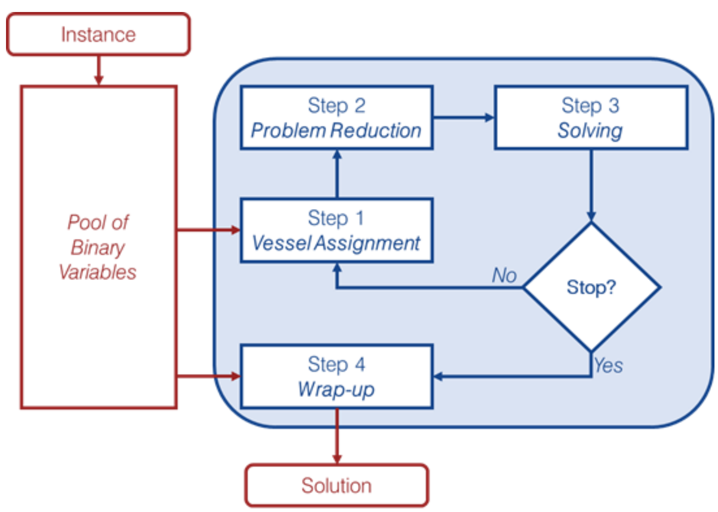



**Figure 6: $\mathcal{ILNS}$ metaheuristic in the blue frame with the four steps: Vessel Assignment step, Problem Reduction step, Solving step, and Wrap-up step.**

Before returning a solution, $\mathcal{ILNS}$ takes a PSIMVA instance and iterates over four steps: the *Vessel Assignment* step, the *Problem Reduction* step, the *Solving* step, and the *Wrap-up* step. In the *Vessel Assignment* step, after partitioning the time horizon into smaller time intervals (e.g., weeks), we assign each vessel to a time interval. Using these assignments, we reduce the pool of binary variables related to vessel assignment in the *Problem Reduction* step. Then, we solve the reduced problem in the *Solving* step. We keep iterating over the time horizon, using previous solutions as a warm-start until completion. Before returning a solution, in case there are still unfulfilled vessels, we try to fulfill them in the *Wrap-up* step. Further details are available in Er Raqabi et al. (2023b). Compared to the standard LNS, which does not work efficiently for very large-scale optimization problems, $\mathcal{ILNS}$ destroys only the part of the solution that can be improved. This is because we do not have time for backtracking in such a huge MILP problem. Thus, we break the problem down, solve it, fix part of the solution, and move forward to improve that solution further. Using $\mathcal{ILNS}$ enhanced by the best configuration returned by $\mathcal{MPILS}$, the solver quickly reaches near-optimal solutions with a time reduction factor of 3 compared to the $\mathcal{MPILS}$ tuner (on the instances from the Jorf site). Given the rapid optimization feature, the $\mathcal{ILNS}$ allows testing several what-if scenarios and strategies.

## PBD method

In the project's third phase, we seek to identify what is left to improve and close the gap, i.e., reach optimality. Thus, we have been leveraging insights from the first two phases to tackle the PSIMVA exactly. Observing that, when fixing some complicating binary variables in the PSIMVA, the solution process became more efficient, and we ended up developing the $\mathcal{PBD}$, a new variant of the Benders decomposition (BD) (Benders, 1962). Compared to $\mathcal{ILNS}$, which selects variable subsets heuristically, $\mathcal{PBD}$ selects subsets by mathematical optimization without suffering computationally and can modify these subsets of variables up to optimality. It is worth highlighting that the complicating variables added to the subproblem are not fixed, as in BD. Thus, the subproblem is a restriction of the original problem and this is why $\mathcal{PBD}$ is primal.

The main insight of PBD is starting with an initial point of complicating variables and gradually inserting promising complicating variables until convergence, as shown in Figure 7. To accelerate our method, we consider a reduced restricted master problem ($RRMP$) and one or several reduced subproblems ($RPSP$) instead of the original ones in BD. We start by constructing an initial point (e.g., obtained using $\mathcal{MPILS}$ tuner). Then, we solve the $RPSP$ and obtain the corresponding Benders cut. After that, we solve the $RRMP$. Using the latter dual solution, we select the most promising complicating $y$ variable based on a reduced cost formula. If a promising complicating $y$ variable is identified, we add it to the $RPSP$ and the $RRMP$ (including lifting the Benders cuts already added). The cycle continues until no promising complicating $y$ variable is identified by the $RCP$. Being primal, $\mathcal{PBD}$ avoids the zigzagging (of the upper bound for minimization problem) behavior of BD. It generates only optimality cuts and uses previous iteration solutions to warm-start the current iteration. We show that $\mathcal{PBD}$ outperforms BD on several academic problems, such as the facility location problem (Drezner and Hamacher, 2004). For this generic problem, we prove optimality in a few cuts instead of thousands of cuts generated by BD. Further details are available in Er Raqabi et al. (2023a). Beyond the OCP case, we designed $\mathcal{PBD}$ specifically to tackle several general large-scale optimization problems.

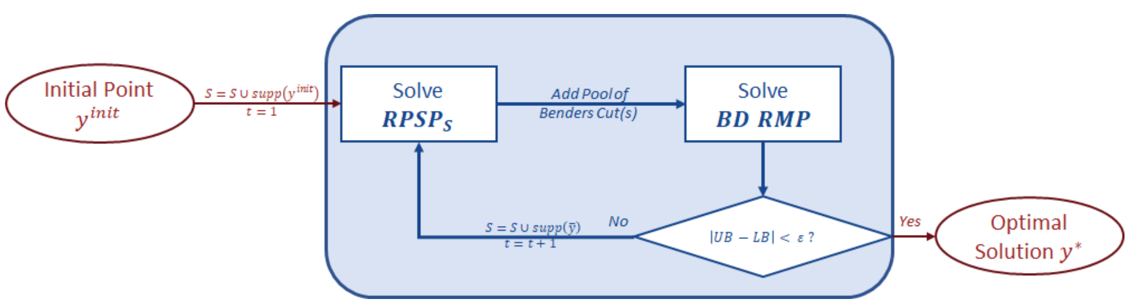



**Figure 7:** $\mathcal{PBD}$ **method in the blue frame.**

## RRO approach

Perturbations are frequent in supply chains. It is the case for the OCP Group, which faces several weather and vessel perturbations on the port side. For instance, when the weather is bad, the loading of vessels is postponed. Also, there are usually delays in vessel arrival. All these aspects significantly affect the schedules obtained using the $\mathcal{MPILS}$ tuner, $\mathcal{ILNS}$ Metaheuristic, or $\mathcal{PBD}$ method. To remain resilient to perturbations and adapt to changing circumstances and challenges in real-time, the OCP Group needed to design an efficient re-optimization approach.

We developed the $\mathcal{RRO}$ approach highlighted in Figure 8. To allow OCP to remain resilient, we define and model resilience. OCP defines resilience as the ability to recover or reach a better schedule $q^*$ while remaining as *close* as possible to the previously optimal schedule $\not{q}^*$. By *close*, we imply fulfilling as many vessels as schedule $\not{q}^*$ while maintaining the least distance possible to this schedule. Following that, we identify and model perturbation(s), which we classify into weather or vessel perturbations. A weather perturbation occurs when the weather in the port is bad enough to affect normal operations. A vessel perturbation occurs when a vessel's arrival at the port is delayed. Then, we identify the set of decisions to take. Within OCP Group, we distinguish two main decisions: the delay decision taken when the weather at the port is bad or when a vessel is delayed, and the advance decision that occurs to allow loading a vessel ahead of schedule. These decisions update the decision variables of the model. For instance, if a vessel is delayed, only its possible (after its arrival date) binary variables are kept in the model. Following these aspects, we formulate the re-optimization problem to maximize resilience. We refer to this first stage as the *problem definition* stage.

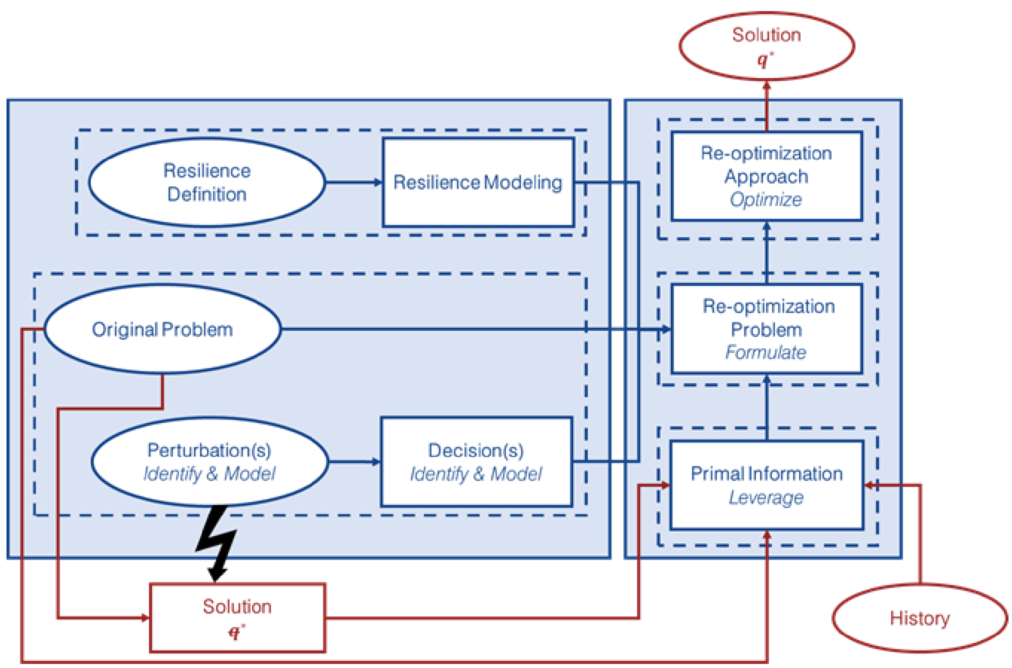



**Figure 8: $\mathcal{RRO}$ approach in the blue frames.**

After formulating the re-optimization problem, we design the re-optimization approach while leveraging the primal information using the previously optimal schedule, the original problem, and the company's history (e.g., previous vessels' assignments to quays and previous production schedules). Such information is relevant since we do not want to optimize from scratch. The qualification primal is borrowed from the optimization lexicon and is used mainly to distinguish between dual and primal methods. The former does not consider the accumulated information in the optimization process, while the latter leverages the accumulated information to reach optimality quickly. Since the perturbations happen on the port side, we fix the production and optimize locally by considering just the port variables and constraints in the re-optimization problem formulation. We quantify resilience and model it as a weighted-objective function to maximize in the re-optimization problem. With local optimization, the re-optimization approach allows reaching schedules as *close* as possible to the previously optimal ones and hence causes the least amount of changes in response to the perturbations. We refer to this second stage as the *re-optimization* stage. Further details are available in Er Raqabi et al. (2023c). Similarly to the $\mathcal{MPILS}$ tuner and the $\mathcal{PBD}$ method, we designed the $\mathcal{RRO}$ approach to tackle several general large-scale re-optimization problems.

## Implementation

Using the four-step solution approach previously described, we were able to generate satisfactory schedules early (using the $\mathcal{MPILS}$ tuner) while improving them gradually via $\mathcal{ILNS}$ metaheuristic. Each algorithmic solution corresponds to a work package with fixed delivery deadlines and intermediate milestones. At the end of each work package, we presented an overview of the methodology and the results obtained on PSIMVA instances. After obtaining approval, implementation was conducted first in the laboratory and then in the DLP on-site for deployment.

**Timeline.** The project started officially in January 2020, and implementation began in September 2020. As per Figure 9, The $\mathcal{MPILS}$ work package became operational towards the end of 2020. It has been used for more than two years within OCP's Jorf site. The $\mathcal{ILNS}$ work package became operational towards the end of 2021 and has been used for more than one year so far within the same site. We continue to refine the system, with extensions forthcoming to cover the addition of new constraints, new variables, and new objectives. Future plans include the delivery and the deployment of the $\mathcal{PBD}$ and $\mathcal{RRO}$ work packages. While the developed solutions have been implemented in the Jorf site, it is worth mentioning that we have started adapting them for other OCP sites and that the first results at these sites are promising.

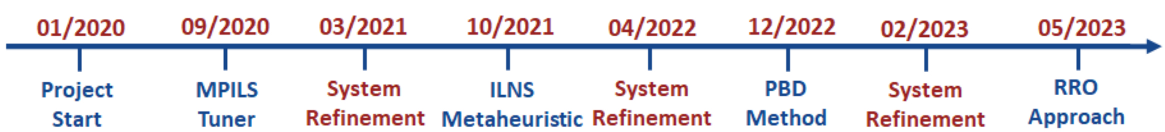



**Figure 9: A timeline of the adoption of OR methods for Production, Inventory, and Vessel Scheduling at OCP group.**

The full-scale system required certain features to make it usable. To implement our solutions within *DLP*, we interfaced it with existing OCP Group databases, manipulated the data into a structured form, built additional pre- and post-processing modules, and generated user-friendly output for the planners. We used the ILOG CPLEX Callable Library and the C++ and R programming languages. Similar to the exploration, we faced several technical and organizational challenges during the implementation.

**Technical challenges.** To successfully tackle the PSIMVA using the *DLP* optimizer, we had to overcome vital system and modeling obstacles. Initially, we developed all the algorithmic solutions locally (in the laboratory), given our restricted access to the *DLP* optimizer. Therefore, testing the algorithms on-site was not possible. Thus, from a system standpoint, the challenge was operationalizing the *DLP* optimizer via methods incorporation. From a modeling standpoint, the challenge was the integrated optimization of production scheduling, inventory management, and vessel assignment with multiple conflicting objectives (e.g., total fulfillment, changeovers, safety stocks, etc.) and their alignment with the real world. In fact, despite their high quality, the solutions returned by the developed approaches sometimes conflicted with what was practical, making them impossible to implement. Thus, we had to work more closely with OCP planners to ensure the validity of the obtained solutions and their implementability. We had identified tacit operational rules not modeled in the PSIMVA. For instance, at OCP, the same product can be produced by different production units. Still, products supplied by different units usually have minor differences in some characteristics, such as color. Unfortunately, this is not acceptable to some customers. Thus, we incorporated new constraints to meet customers' requirements and ensure the solutions' validity (Er Raqabi et al. 2023b).

**Organizational challenges.** Over the project, we have been working on creating a good mood and increasing confidence in the project whenever possible. We welcomed skepticism over the *DLP* optimizer and the algorithmic developments, and gradually earned the planners' support, bolstering the *DLP*'s acceptance. Prototyping with a rapid cycle and the resulting quick feedback to the end user promoted this acceptance. We were also fortunate to gain the active participation of some planners with a background in OR. They worked with us to validate the *DLP* plans and served as advocates by convincing fellow planners that they could become more effective using the optimizer.

On the senior level, each half a year, senior managers required us to justify continuing the OCP-Poly-UM6P research effort. The approval process is not simple, and we have to document the details of our research. The Poly researchers' reputation and early successes also carried weight in ensuring the continuation of the project. Most importantly, we have maintained an open and honest dialogue with OCP managers about our progress, discussing the ups and the downs. We took every opportunity to empirically demonstrate the payoffs to the company, clearly demonstrating the system's possible uses and organizational impact.

## Impact

As mentioned above, each step detailed above corresponds to a work package to be delivered within agreed-upon deadlines. The delivery of the $\mathcal{MPILS}$ and $\mathcal{ILNS}$ work packages have reduced OCP's supply chain costs and the way planners schedule tasks. In addition, the operations planning team has frequently used our solutions to support the planning process. We categorize the project's widespread impact into four areas: quantifiable benefits, planning process, theory versus practice, and visibility and portability.

**Quantifiable benefits.** The developed solutions allowed us significantly reduce the time metric while increasing the quality metric. The system, designed for weekly use at each industrial site, works as follows: The planner updates the necessary planning data for a 4-week horizon and provides a scenario to the *DLP* optimizer, which returns the best schedule of production, stock, and loading found. To do so, the latter operates according to an interactive *model-based approach*. Each model is a file containing a script with several parameters, including the method ($\mathcal{MPILS}$, $\mathcal{ILNS}$, or $\mathcal{PBD}$), execution time, stopping criterion, and the number of iterations. There is also an option where several models can be run iteratively. If activated, the best solution found by the current model is provided as a warm-start to the subsequent model. For instance, the user may run a first model with the $\mathcal{MPILS}$ best configuration until reaching a satisfactory initial solution (e.g., a gap below a threshold). Then, the user can provide the latter as a warm-start to a second model where $\mathcal{ILNS}$ is run to find a near-optimal solution. If the user seeks optimality, the near-optimal solution can be provided as a warm-start to a third model where the $\mathcal{PBD}$ method is run to find the optimal solution. This model-based approach allows enough flexibility for the user to change parameters and run various models, making it implementable in practice.

After analyzing the business processes with the OCP management, we discovered that the KPIs can be prioritized. Thus, instead of using the weighted sum method for multiobjective optimization, we relied on the most appropriate method, i.e., the lexicographic method (Marler and Arora, 2004). We consider in this section two main KPIs used by OCP Group: Total Fulfillment (TF) and Product Changeovers (PC). Our developed algorithms are used to maximize TF at the first stage. Then, we minimize PC in the second stage. More details can be found in Er Raqabi et al. (2023b).

We highlight below the computational results on eight PSIMVA instances from the main OCP site, the Jorf site (J instances). We report on Table 1 averages of the scheduling horizon (in days), the number of vessels, the demand (in tonne), the number of variables, integers, binaries, and constraints.

**Table 1: PSIMVA instances description.**

| *Instance* | *Horizon* | *Vessels* | *Demand* | *Variables* | *Integers* | *Binary* | *Constraints* |
|---|---|---|---|---|---|---|---|
| J-1 | 32 | 48 | 1320580 | 470310 | 170772 | 12314 | 1560843 |
| J-2 | 32 | 62 | 2031400 | 947598 | 366330 | 17966 | 3506473 |
| J-3 | 32 | 61 | 1066290 | 936657 | 359570 | 11155 | 3610913 |
| J-4 | 24 | 40 | 1043330 | 298693 | 142362 | 33284 | 1489253 |
| J-5 | 30 | 58 | 1797910 | 450772 | 192268 | 15144 | 1964908 |
| J-6 | 30 | 58 | 1797910 | 450772 | 192276 | 15237 | 1964908 |
| J-7 | 30 | 58 | 1740100 | 450789 | 192292 | 15237 | 1957865 |
| J-8 | 32 | 61 | 957338 | 948009 | 360419 | 18264 | 3679588 |
| **Avg** | **30** | **56** | **1469357** | **619200** | **247036** | **17325** | **2466844** |

For each instance and for the first KPI (TF), we report in Table 2 the *Time* (in seconds) and the *Quality* (integrality gap in %) using the initial *DLP* and the current *DLP*. For the current *DLP*, we report the *Method* that returned the best solution. We allocate 10 hours and 10 minutes for the initial *DLP* and the current *DLP*, respectively. As seen in Table 2, we obtain near-optimal (if not optimal) solutions in a short amount of time using the developed solution methods on the first KPI. On average, the time reduction factor is around 66 for the Jorf site.

**Table 2: Results obtained on J instances using the initial DLP and the current DLP for the TF KPI.**

| *Instance* | *Initial DLP* | | *Current DLP* | | *Method* |
|---|---|---|---|---|---|
| | *Time* | *Quality* | *Time* | *Quality* | |
| J-1 | 36000 | 15.2 | 317 | 0.0 | $\mathcal{MPILS}$ |
| J-2 | 36000 | 17.5 | 458 | 0.0 | $\mathcal{MPILS}$ |
| J-3 | 36000 | 23.4 | 600 | 0.0 | $\mathcal{ILNS}$ |
| J-4 | 36000 | 25.7 | 600 | 0.0 | $\mathcal{ILNS}$ |
| J-5 | 36000 | 29.9 | 600 | 1.4 | $\mathcal{ILNS}$ |
| J-6 | 36000 | 32.9 | 600 | 1.9 | $\mathcal{ILNS}$ |
| J-7 | 36000 | 34.6 | 600 | 2.1 | $\mathcal{ILNS}$ |
| J-8 | 36000 | 34.9 | 600 | 2.3 | $\mathcal{ILNS}$ |
| **Avg** | **36000** | **26.8** | **547** | **1.0** | |

After maximizing TF, we minimize the second KPI (PC). We report in Table 3 the *Time* (in seconds) and the *Quality* (number of product changeovers) using the initial *DLP* and the current *DLP*. For the initial *DLP*, we recall that it relies on a weighted sum objective function. Thus, we collect the PC obtained after 10 hours. We allocate 10 minutes for the current *DLP*.

**Table 3: Results obtained on J instances using the initial DLP and the current DLP for the PC KPI.**

| *Instance* | *Initial DLP* | | *Current DLP* | |
|---|---|---|---|---|
| | *Time* | *Quality* | *Time* | *Quality* |
| J-1 | 36000 | 0 | 1 | 0 |
| J-2 | 36000 | 0 | 2 | 0 |
| J-3 | 36000 | 4 | 17 | 0 |
| J-4 | 36000 | 4 | 13 | 2 |
| J-5 | 36000 | 4 | 18 | 2 |
| J-6 | 36000 | 4 | 20 | 2 |
| J-7 | 36000 | 8 | 22 | 2 |
| J-8 | 36000 | 12 | 31 | 2 |
| **Avg** | **36000** | **5** | **16** | **1** |

As can be seen in Table 3, we obtain optimal solutions quickly. After maximizing TF in the first stage, PC minimization becomes easy. On the other hand, the initial *DLP* does not reach optimality in all instances. The $\mathcal{MPILS}$ and $\mathcal{ILNS}$ are sufficient to reach optimality on several PSIMVA instances. The $\mathcal{PBD}$, still under experiments in the lab, will be sufficient to close the gap for the most complex ones. Financially speaking, these algorithmic solutions have allowed for the operationalization of the *DLP* optimizer, which was a bottleneck curbing the usage of many other supply chain management tools (e.g., pricing, mine extraction, logistics, customer relationship management, etc.). These tools are linked since there is no point in producing more of a product if it cannot be delivered to the end customer. For instance, the use of OCP's enterprise resource planning (SAP) is strongly linked to the outputs of the *DLP*. The production and stock orders managed in the SAP system generally result from a conversion of the proposals established by the optimizer. After each planning optimization, the *DLP* tool communicates production and stock proposals to the SAP system in the form of *planned orders* and *stock requisitions*. These proposals will then be checked, tuned, and validated by the production and stock managers before being fixed within the SAP system. After *DLP* operationalization, many tools used by OCP's various departments became more effective as well, thus allowing OCP to increase its annual turnover by around +5%. Such an increase is equivalent to 240 million dollars, as witnessed by the industrial partner verification letter. We recall that the successful *DLP* operationalization took place within the Jorf Lasfar site. While there are still other OCP sites, the impact is already significant since the Jorf site is the largest among all sites, with 90% of total production.

**Planning process.** The *DLP* operationalization has led to a shift from manual to mathematically-based planning and scheduling, significant time savings, and human error reduction. With its quick (from a practical perspective) optimization capability, the *DLP* optimizer becomes an efficient decision-making tool to check, simulate, and re-optimize schedules. It also supports the supply chain in becoming more resilient to unexpected events and risks via what-if scenarios simulations. These events include the management of vessels, the weather in the port, and machine breakdown.

The first case of the planning process is related to the management of vessels. The planning division usually incorporates two types of vessels: confirmed and unconfirmed. Confirmed vessels are those for which the vessels are expected to arrive at a specific interval, while unconfirmed vessels are those that will have to be fulfilled, but for which the vessel arrival schedule has not yet been fixed. They may be delayed or even canceled. Instead of considering the whole set of vessels, the provided solutions allow the iterative insertion of vessels according to their confirmation status. This gives rise to a layer-based optimization process, where each layer restrictively contains the confirmed vessels. Schematically, after decomposing the time horizon into smaller time intervals, we start solving a restricted model focusing first on the confirmed vessels. Then, the unconfirmed ones can be added to the model once they are confirmed, and a new re-optimization solving, using the best available integer solution as a warm-start, is carried out. A visualization of these two layers is illustrated in Figure 10.

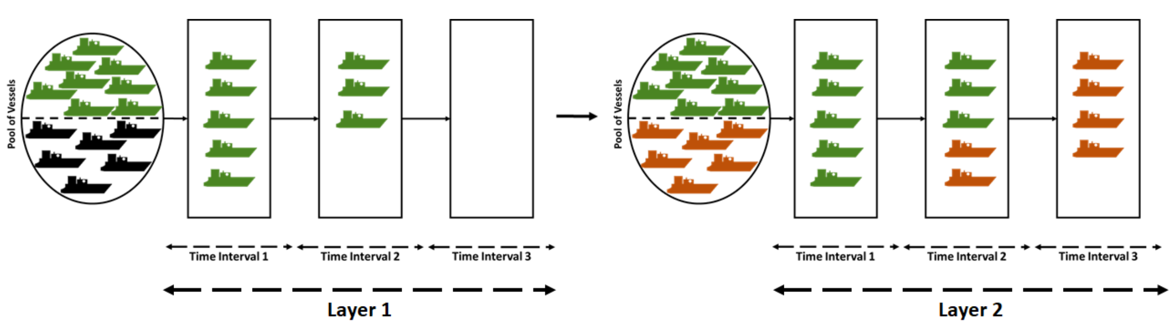



**Figure 10: A layer-based optimization example with two layers.**

The first optimization layer deals with the confirmed vessels (in green), while the second optimization layer deals with the unconfirmed vessels (in black) that have become confirmed (in orange). As shown, the first layer solution is kept as a starting point for the second layer. This is an efficient way to leverage the available information and incorporate new information once it becomes available. The company can also plan the first time interval(s) deterministically since reliable information is usually available, and relax the planning of the remaining uncertain intervals. This can be done in several ways, including relaxing all binary variables or considering representative aggregated variables for uncertain intervals.

In Table 4, we present an example in which we consider both confirmed and unconfirmed vessels in a small set of instances. We compare the scenario where we conduct a layer-based optimization with the one where we take into consideration all vessels at once (like in Table 2). In the former, we optimize only the confirmed vessels in each layer using $\mathcal{ILNS}$. We report the number of confirmed vessels (# Conf.), the fulfillment percentage of confirmed vessels (% Conf.), the number of unconfirmed vessels (# Unconf.), and the fulfillment percentage of unconfirmed vessels (% Unconf.). In the first layer, we report the number of confirmed vessels, and in the second layer, the subsequently confirmed vessels (initially unconfirmed in the first layer).

**Table 4: Re-optimization example when considering confirmed and unconfirmed vessels.**

| Instance | Vessels | Layer 1 | | Layer 2 | | Vessels | | | | No Layer | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | # Conf. | % Conf. | # Conf. | % Conf. | # Conf. | % Conf. | # Unconf. | % Unconf. | % Conf. | % Unconf. |
| J-1 | 34 | 19 | 100.0 | 10 | 100.0 | 29 | 100.0 | 5 | 0.0 | 100.0 | 100.0 |
| J-2 | 62 | 36 | 100.0 | 10 | 100.0 | 29 | 100.0 | 3 | 0.0 | 100.0 | 100.0 |
| J-3 | 61 | 34 | 100.0 | 18 | 100.0 | 52 | 100.0 | 9 | 0.0 | 100.0 | 100.0 |
| J-4 | 40 | 22 | 100.0 | 12 | 100.0 | 34 | 100.0 | 6 | 0.0 | 100.0 | 100.0 |
| J-5 | 58 | 32 | 100.0 | 17 | 100.0 | 49 | 100.0 | 9 | 0.0 | 95.0 | 100.0 |
| J-6 | 58 | 39 | 100.0 | 17 | 100.0 | 56 | 100.0 | 2 | 0.0 | 87.5 | 100.0 |
| J-7 | 58 | 40 | 100.0 | 16 | 100.0 | 56 | 100.0 | 2 | 0.0 | 91.1 | 100.0 |
| J-8 | 61 | 32 | 100.0 | 26 | 100.0 | 58 | 100.0 | 3 | 0.0 | 91.4 | 100.0 |
| **Avg** | **54** | **32** | **100.0** | **17** | **100.0** | **49** | **100.0** | **5** | **0.0** | **95.6** | **100.0** |

The main issue when considering all vessels at once is that possibly unconfirmed vessels may be fulfilled instead of confirmed ones. As observed in Table 4 for J instances, when considering all vessels at once, on average, 95.60% of confirmed vessels are fulfilled while 100.00% of unconfirmed ones are fulfilled. On the other hand, using layer-based optimization, all of the confirmed vessels are fulfilled, with 32 and 17 vessels fulfilled in the first and second layers, respectively. When optimizing based on the confirmation status, we ensure that possibly unconfirmed vessels will not be prioritized over confirmed ones, thus allowing more opportunities to fulfill the confirmed vessels. Furthermore, the layer-based optimization schedule is more robust because unconfirmed vessels are subject to cancellations and, therefore, could cause more disruptions.

**Theory versus practice.** While we have been using OR theory to inform practice, this project generated new theoretical and methodological insights from practice. Indeed, we developed the $\mathcal{MPILS}$ tuner, which is generic and scalable to other solvers; the $\mathcal{ILNS}$, which can be adapted and applied to various contexts; and lastly the $\mathcal{PBD}$, opening new research paths and horizons in BD. Beyond the cited papers (Himmich et al., 2023; Er Raqabi et al., 2023b; Er Raqabi et al., 2023a; Er Raqabi et al., 2023c), the algorithmic solutions are expected to generate new and relevant insights both theoretically and methodologically.

**Visibility and portability.** We wrote papers, participated in conferences, and obtained research excellence scholarships. The success story of OCP and UM6P as an African hub of research and development in agriculture and fertilizers is encouraging other partner African countries to leverage investments in research and development.

## Involvement of local researchers

The stakeholders contributing to this project are OCP Group, UM6P, and Polytechnique Montreal (Poly) from Canada. Local researchers with a solid background (Ph.D.) in OR and logistics include the OCP and UM6P researchers, many of whom also belong to multiple Moroccan universities. Together with these researchers, we overcame several challenges. Being multidisciplinary and complementary (industrial engineering, logistics, large-scale optimization methods), we have ensured the alignment between academic developments and their practical applicability on the OCP side. We overcame all challenges and obstacles with the support of local researchers. Without them, this project would have been a failure.

**UM6P researchers.** UM6P researchers acted as a bridge between us from Poly and OCP. They played a significant role in ensuring smooth progress since the beginning of the project. They actively participated in the definition and delimitation of the problem and proposed optimization approaches adapted to the OCP business. They also contributed to data collection and analysis. On the implementation side, they monitored business testing and validation.

**OCP researchers.** To explore the PSIMVA, researchers and analysts visited OCP sites. OCP researchers hosted our team members and collaborated closely with them. The visits allowed us to align the mathematical model with the real-world perspective, especially since some constraints were not present in all instances of the PSIMVA. We met online when necessary, sometimes 2-3 times a week, to share insights, validate our approach, highlight the obtained results, and obtain feedback. OCP researchers were outgoing during meetings and supported our analysts in accessing OCP Group's ERP (Enterprise Resource Planning). They also popularized many OR concepts to OCP operators and managers without an OR background. As a result of these efforts, the *DLP* optimizer was rescued from obsolescence and is now gaining traction as an efficient planning tool within the OCP Group.

**Learned lessons.** The involvement of local researchers led us to acquire several insights. First, in applied research, system implementation requires effective communication, which cannot happen without local researchers who know the company's culture. These researchers support the popularization of concepts and the validation of solutions. Second, successfully managing the human factor is crucial to the success of applied research. Social understanding is required even if the project is fully applied mathematics. Consequently, African researchers are the most suitable for leading projects related to the African continent because of their knowledge of the application context. Of course, the support of worldwide experts is necessary if there is no local expertise. Without the effective involvement of local researchers, we would have failed like so many others (Scott and Vessey, 2000; Xue et al., 2005; Danışman, 2010; Garg and Garg, 2013). The lessons learned highlight the importance of aspects related to the human factor when deploying optimization systems. These aspects are generally missing when learning optimization.

## Conclusion

Despite being considered obsolete for several years, the *DLP* optimizer has gained another lease on life to become an efficient planning tool for OCP Group. After overcoming several challenges and developing the $\mathcal{MPILS}$ tuner, the $\mathcal{ILNS}$ metaheuristic, and the $\mathcal{PBD}$ method, we were able to operationalize the optimizer. Thanks to these improvements, the *DLP* should contribute to increasing OCP's turnover by more than $240 million per year. The long-term impact might far exceed these estimates, as changes produced by the optimizer affect the whole supply chain and the different OCP sites, generating more profits and gains. Once again, operations research has demonstrated its capacity to enhance processes that directly improve the lives of humans.

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