A Novel Approach to Scheduling Water Injection for Energy Efficiency in Ghawar Oilfield

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Abstract

Optimizing water injection processes in oil production is crucial for reducing energy consumption and operational costs. This paper considers the problem of optimally operating seawater injection for the Ghawar oilfield, unequivocally the world's largest conventional oilfield. Focusing on a complex water distribution and injection network, which draws millions of barrels daily from the Arabian Gulf, the model utilizes mixed-integer linear programming to minimize operational costs. It prescribes optimal daily injection rates at each flank, efficient pump operational parameters, and supply strategies for swing flanks. The model accommodates user-defined constraints, ensuring month-end compliance targets are met. By introducing penalty terms in the objective function, the model minimizes daily operational variations, producing a practical and operationally acceptable schedule. Employing techniques to enhance computational efficiency, the model reduces CPU times from hours to an average of 340 seconds. Results demonstrate the model’s ability to reduce energy consumption for the water injection network by up to a 7%, yielding an implementable schedule with minimal disruptions and accordingly a significant reduction in GHG emissions.

**Keywords**: seawater, injection, optimization, emissions, energy.

* 1. Introduction

In the world of oil production, the injection of substantial volumes of seawater into subterranean reservoirs plays a pivotal role in maintaining pressure and enhancing oil recovery. Accordingly, the potential for optimizing this process to reduce energy consumption and operational costs is a compelling challenge. While numerous studies explored various aspects of oilfield optimization, a noticeable gap exists in the literature regarding the comprehensive optimization of water injection networks in giant fields.

Liu et al. (2016) addressed the optimal operation of a network of gas oil separation plants (GOSPs) in the Arabian Gulf Coast Area. Their mixed integer linear programming (MILP) model optimizes crude transfer through swing pipelines, showcasing potential cost savings in operating expenditures. On the other hand, addressing the issue of energy consumption in high water-cut reservoirs, Bai et al. (2021) presented an integrated energy-consumption calculation model. Leveraging a Particle Swarm Optimization algorithm and reservoir numerical simulation, their model showcased notable reductions in energy consumption. Gas lift optimization, a crucial aspect for maximizing crude oil production from well platforms, is highlighted by Sudhanshu and Chaturvedi (2021). Their approach, utilizes regression and linear programming based on field data to allocate compressed gas to wells.

In the domain of strategic/tactical planning of offshore oilfield development, Gupta and Grossmann (2012) presented a multiperiod nonconvex mixed-integer nonlinear programming (MINLP) model. Originally designed for offshore fields, this model offers versatility for optimizing infrastructure and production planning over long-term horizons. In continuation of this work, Awasthi and Grossmann (2019) provided insights into multiperiod optimization models for oilfield production planning. Their models emphasized the significance of multiperiod optimization in oil and gas production planning and introduce a bicriterion optimization model for determining an ideal compromise solution between net present value (NPV) and total oil production.

In the domain of reservoirs waterflooding, Zhou et al. (2019), amongst a few others, developed optimization models for optimal flooding strategy and control of a surface waterflooding pipeline network. However, in their approach, the total profit of waterflooding development was defined as the objective function and they did not consider the potential of minimizing energy consumption of surface equipment.

In this paper, we introduce a pioneering model to optimize the daily scheduling of a water injection network in the Ghawar oilfield. This network comprises a multitude of nodes, where seawater first undergoes a series of preliminary treatments. The treated seawater is then pumped through an extensive network of plants, which either further pressurize the water for transfer to other plants or directly inject it underground through remote wells, which are located along piping flanks. Notably, certain flanks can be supplied by multiple injection plants. Our model offers optimal guidance on daily injection rates for each flank, ensuring the fulfillment of month-end compliance targets. It prescribes the most efficient operational parameters for each pump, should they be selected by the optimizer for use, and outlines the optimal supply strategy for swing flanks. Furthermore, it allows for the incorporation of user-defined constraints, such as specifying the maximum number of days with no injection.

*Figure 1 Ghawar Oilfield Water Injection Network*

* 1. Problem Definition

The starting point of the water injection network is the Qurayyah Seawater Plant, located on the Arabian Gulf (Figure 1). The facility is capable of processing some 14 million barrels of seawater daily, more than any other comparable water treatment facility in the world. The treated water leaves Qurayyah south bound to the ‘Uthmaniyah Water Supply Plant (UWSP) and north to the Ain Dar Water Injection Plant (ADWIP). From UWSP, water is pumped to a network of water injection plants (WIPs). Each WIP directs water to a number of remote injection wells located along flanks.

*Table 1 Equipment at Water Injection Plants*

|  |  |  |  |
| --- | --- | --- | --- |
| Plant/Equipment | Gas Turbine Pump | Motor Pump | Capacity (Thousand Barrels per Day - MBD) |
| UWSP | 6 | - | 970 - 1900 |
| UWIP-1 | 2 | - | 384 - 450 |
| UWIP-3 | 3 | - | 205 - 350 |
| UWIP-4 | 4 | - | 205 - 350 |
| UWIP-5 | 4 | - | 205 - 350 |
| HAWIP | 6 | - | 240 - 500 |
| HAWIP Shipping | - | 3 | 335 - 665 |
| ADWIP | 4 | - | 420 – 680 |
| ADWIP Shipping | - | 3 | 620 – 1570 |
| SRF | - | 4 | 85 – 150 |

Four ‘Uthmaniyah WIPs sustain pressure in the Ghawar’s North section, while the Hawiyah WIP (HAWIP) injects to wells that are connected directly to it and additional ones further south at HRDH. In the North, water is pumped to the Sulfate Removal Facility (SRF) and ADWIP. At ADWIP water is directed to remote injection wells and is also sent to Khurais Central Processing Facility (KhCPF), which is responsible for injecting water at the Khurais field.

 Each WIP is equipped with a set of motor or gas turbine driven pumps with varying minimum and maximum capacities (Table 1). Each WIP is connected to a set of flanks. In this work, we do not model wells explicitly and will group their assigned production targets into their respective flanks. Two flanks are shared between UWIP-1 and UWIP-3. One Flank is shared between UWIP-4 and HAWIP and one flank is shared between UWIP-5 and HAWIP. The objective of this work is to build a model which minimizes the overall energy consumption of the network. It shall issue a schedule with minimal disruptions both in the pumping and injection rates. This is crucial for the usability of the models and the applicability of the results as it is not preferred to frequently adjust the injection flowrate for each well or flank. It is also possible to shutdown injection for a given maximum number of days. If not shutdown, the flank must operate between given minimum and maximum rates. It is also mandatory to meet month end total targets within a given compliance limit, which can be separately specified for each flank. For this work, it is assumed that if pumps are used, the model will sustain a fixed base cost, which varies per pump, but is not a function of the flowrate.

* 1. Mathematical Model

Our mathematical model has a MILP formulation with binary and continuous variables. Its objective is to minimize the cost of operating the network, which is primarily composed of running injection pumps. This is in addition to various terms that aims to make the schedule practical and implementable.

|  |  |
| --- | --- |
| Min $$\sum\_{t}^{}\sum\_{f}^{}y\_{t,f}^{inject}$$ | (1) |

$$+$$

$$+$$

$$-$$

$$\sum\_{t}^{}\sum\_{f}^{}x\_{t,f}^{DIR}$$

$$\sum\_{t}^{}\sum\_{p}^{}x\_{t,p}^{DPR} $$

$$\sum\_{t}^{}\sum\_{p}^{}z\_{t,p}^{pumps}×Cost\_{p}^{WIP}$$

subject to

$$-$$

|  |  |
| --- | --- |
| $$∀ t\in T, p\in P$$$$x\_{t,p}^{pump rate} \leq   z\_{t,p}^{pumps} ×MaxRate\_{p}^{WIP}$$ | (2) |
| $$\sum\_{p}^{ } x\_{p,f,t}^{supply}\geq  MinRate\_{f}^{flank} × y\_{t,f}^{inject}$$$$∀ t\in T, p\in P$$$$x\_{t,p}^{pump rate} \geq   z\_{t,p}^{pumps} ×MinRate\_{p}^{WIP}$$ | (3) |
| $$∀ t\in T,f\in F$$$$∀ t\in T,f\in F:\left(p,f\right) in active\\_routes$$ | (4) |
| $$∀ t\in T,f\in F$$$$\sum\_{p}^{ } x\_{p,f,t}^{supply}\leq  MaxRate\_{f}^{flank} × y\_{t,f}^{inject}$$ | (5) |
| $$\sum\_{p}^{ } x\_{p,f,t}^{supply}=  0$$$$∀ t\in T^{\*},f\in F$$ | (6) |
| $$∀ t\in T, p\in P $$$$\sum\_{f}^{} x\_{p,f,t}^{supply}= x\_{t,p}^{pump rate}$$ | (7) |
| $$∀ f\in F$$$$\sum\_{t}^{}1-y\_{t,f}^{inject} \leq MaxZeroFlowDays\_{f}$$ | (8) |
| $$\sum\_{p}^{ } x\_{p,f,t+1}^{supply}-x\_{p,f,t}^{supply} \leq  x\_{t,f}^{DIR} $$$$∀ f\in F,$$$$\sum\_{t}^{}\sum\_{p}^{}x\_{p,f,t}^{supply}\geq \left(1-MaxDev\_{f}\right) × \sum\_{t}^{} InitialRate\_{f,t}^{flank}$$ | (9) |
| $$\sum\_{p}^{ } x\_{p,f,t}^{supply}- x\_{p,f,t+1}^{supply}\leq  x\_{t,f}^{DIR} $$$$∀ f\in F$$$$∀ t\in [0,1,..,T-1]$$$$∀ t\in [0,1,..,T-1]$$ | (10) |
| $$∀ f\in F$$ | (11) |
| $x\_{t+1,p}^{pump rate}-x\_{t,p}^{pump rate}\leq    x\_{t,p}^{DPR}$ $$∀ p\in P$$$$∀ t\in [0,1,..,T-1]$$$$∀ p\in P$$$$∀ t\in [0,1,..,T-1]$$ | (12) |
| $x\_{t,p}^{pump rate}- x\_{t+1,p}^{pump rate}\leq  x\_{t,p}^{DPR}$ $$x\_{t}^{UWSP}= \sum\_{p}^{}x\_{t,p}^{pump rate}$$ | (13) |
| $$p\in [UWIP-1, UWIP-3, UWIP-4, UWIP-5, HAWIP, HAWIP Shipping] $$$$∀ t\in T$$ | (14) |

Sets T, P and F refer to time periods, WIPs and flanks, respectively. Variables x, y and z refer to continuous, binary and integer variables, respectively.

The first term in Eq. (1) calculates the total cost of used pumps at each WIP, where $z\_{ }^{pumps}$ is the number of running pumps at the WIP and $Cost\_{ }^{WIP}$ is the cost of using a pump, which is assumed to be the same for all pumps at the same WIP to reduce the problem size. The second term penalizes the model for setting zero injection rate at a given day to avoid unnecessary shut down of injection, where $y\_{ }^{inject}$ is a binary variable which is activated when there is zero injection. The third and fourth terms minimize fluctuations in injection and pumping rates, respectively, where $x\_{ }^{DIR}$ is a variable that equals or exceeds daily variations in injection rates and $x\_{ }^{DPR}$ is defined to equal or exceed daily variations in pumping rates as will be illustrated in the constraints.

The constraints in Eqs. (2) and (3) ensure that the total supply of each WIP falls between the aggregated minimum and maximum limits of operating pumps, where $x\_{ }^{pump rate}$ is the water rate supplied by a given WIP. $MaxRate\_{ }^{WIP}$ and $MinRate\_{ }^{WIP}$ are the maximum and minimum rates of pumps at each WIP, which are assumed to be equal for each pump at each WIP. The constraints in Eqs. (4) and (5) limit the total injection to

|  |  |  |
| --- | --- | --- |
| **Flank** | **Base Supply (MBD)** | **Supplier** |
| 1N-U | 28 | UWIP-1 |
| 1N-S | 102 | UWIP-1 |
| 1N-S-E-S | 99 | UWIP-1/3 |
| 1S-U | 130 | UWIP-1 |
| 1E-U | 41 | UWIP-1 |
| 3N-S W | 59 | UWIP-3 |
| 3N-S W S | 99 | UWIP-3/1 |
| 3N-U | 14 | UWIP-3 |
| 3S-U | 186 | UWIP-3 |
| 4N | 91 | UWIP-4 |
| 4S | 108 | UWIP-4 |
| 4E | 342 | UWIP-4 |
| 5N | 105 | UWIP-5 |
| 5S | 179 | UWIP-5 |
| 5W | 454 | UWIP-5 |
| 5W - S | 46 | UWIP-5/ |
| HAWIP |
| HA-NE | 307 | HAWIP |
| HA-NE S | 38 | UWIP-4/ |
| HAWIP |
| HA-NE SE | 568 | HAWIP |
| HA-HDE-1 | 409 | HAWIP |
| HA-NW | 88 | HAWIP |
| HA-SW | 248 | HAWIP |
| HA-HDW-1 | 270 | HAWIP |
| HA-HD-2E | 185 | HAWIP |
| HA-HD-2W | 241 | HAWIP |
| HA-HD-3 | 576 | HAWIP |
| A-EF | 239 | ADWIP |
| A-WF | 302 | ADWIP |
| SHWIP | 280 | ADWIP |
| NAD | 258 | ADWIP |
| FZRN | 291 | SRF |
| S Injection | 1968 | ADWIP |
| LFDL | 240 | ADWIP |

each flank between the minimum and maximum allowed rates, where $x\_{ }^{supply}$is the supply from each WIP to each flank. They also control for limiting the number of shutdown days by embedding the term $y\_{ }^{inject}$. Eq. (6) ensures that injection to a given flank is zero for user define periods T\*. Eq. (7) balances the supply from each WIP with the rate from its pumps. Eq. (8) limits the number of shutdown days to those defined by the user. Eq. (9) ensures the model meets the month end injection target within a user-defined minimum compliance. Eqs. (10) and (11) activate the variable $x\_{ }^{DIR}$, which is minimized in the objective function to reduce injection fluctuations. Similarly, Eqs. (12) and (13) minimize fluctuations in pump rates. Finally, Eq. (14) ensures the water rate supplied by plant UWSP is equal the water rate of the connected receiving plants. To reduce solve time, we ensured variables are strictly defined between their feasibility limits. We also, added constraints that ensures no more than 2 rate changes are allowed, which is operationally sensible and computationally advantageous. Also, for symmetry breaking, we assigned a cost for shutting down injection to each flank, which increases along the periods in the schedule. This incentivized the model to place any shutdowns in the beginning of the schedule, therefore reducing solve time significantly.

*Table 2 Flanks Supply Case*

The MILP problem was formulated in Python v3.7 using the PuLP library and solved using the COIN CLP/CBC LP solver.

* 1. Results

We conducted multiple experiments to assess the efficacy of the proposed model. Table 2 represent the base schedule. It includes a majority of Ghawar flanks supplied by the model. Injection should be as close as possible to the Base supply.

* + 1. Case (1): Minimum 90% Supply of Base, 95% Month End Deviation and Zero Shutdown Days

In this case, the minimum supply to each flank must be 90% of the base supply, each day and the model must meet 95% of the month-end supply without shutting down injection to any flank. In this case, the model solves in 210 seconds. The model reduces injection to UWIP-1 flanks by 90% for half of the month then ramps up injection to full capacity for the rest of the month. It supplies flank ‘3N-S W S’ for half of the month from UWIP-1 and the other half from UWIP-3. It reduces injection to flank ‘3S-U’ by 9% for half of the month and by 1% for the other half. The model reduced injection to UWIP-4 flanks by 9% for half of the month, then 1% for the other half. UWIP-5 flanks injection was reduced by 9% for half of the month. Overall, this allowed the model to operate 3 pumps at UWSP for half of the month and 4 pumps for the other half, as opposed to 4 pumps throughout the month. It also allowed operating one pump at UWIP-1 throughout the month as opposed to 2 pumps in the base case. This reduces energy consumption by 4.8% in comparison to the base case where 4 pumps at UWSP are operated.

* + 1. Case (2): Minimum 90% Supply of Base, 85% Month End Deviation and one day of allowed shutdown per flank

The major changes in this case include shutting down ADWIP injection for one day then operating at max capacity for the rest of the month. The model also shuts down injection at UWIP-3, 4 and 5 and HAWIP for one day. It then operates at the minimum supply for most of the month. This allows reducing the number of operating pumps at HAWIP to 3 for 2 days and operate 6 for the remainder of the month. It also allows operating 2 pumps at UWSP for 2 days and 3 for the remainder of the month as opposed to 4 in the base case proposed by the user. UWIP-1 behaves similarly as in case (1) but the reduction lasts for the entire month. This allows reducing energy consumption by 8.5%.

* 1. Conclusions

In this work, we developed a first of a kind MILP model for the optimization of water injection operation at the Ghawar field. The model allows uncovering optimization opportunities that would be very challenging to arrive at manually. This results in reducing energy consumption by an average of 7%. The model provides minimal fluctuations in injection and pumping rates. It can also allow for user-defined constraints, such as specifying the number of maximum shutdown days. The formulation results in a model that generates practical and implementable schedule, which supports its usability.

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