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Multicriteria modeling and tradeoff analysis for oil load dispatch and hauling operations at Noble energy

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Abstract Noble Energy produces and sells tens of thousands of barrels of oil a day in the Wattenberg field in northeastern Colorado, one of the largest natural gas deposits in the United States. This paper describes a new mathematical model that was built and implemented to support the company's business decisions regarding its current and future sales, dispatch, and transportation operations. The corresponding multicriteria optimization model is formulated and solved as a multi-period, multi-objective mixed-integer program that considers the maximization of revenue and sales, and the avoidance of temporary production shut-ins and sell-outs to guarantee long-term contractual obligations with its partnering well owners, haulers, and markets. A theoretical tradeoff analysis is presented to validate model decisions with current operational practice, and a small computational case study on an original data set demonstrates the use of this model to find efficient dispatch schedules and gain further insights into the tradeoffs between the different decision criteria.

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1 Introduction

New advances in drilling technologies have made the exploration of oil and natural gas possible in an increasing number of areas. As a result, many deposits that so far remained expensive or technically challenging to reach are now producing energy resources. One such area is the Denver–Julesburg (DJ) Basin situated north of the Denver metropolitan area on the eastern side of the Rocky Mountains in northeastern Colorado and southern Wyoming. The DJ Basin is home to the Niobrara Formation, a massive shale deposit that contains vast quantities of oil and natural gas trapped in small pockets at depths of about 3,000–14,000 feet. While the presence of this resource had been known and produced using conventional techniques for several decades, horizontal drilling has recently unlocked previously non-producible reserves and led to a significant increase in local energy operations. This brings along with it new logistical challenges.

As one of the leading independent energy companies in North America, Noble Energy produces and sells tens of thousands of barrels of oil a day in the DJ Basin's Wattenberg field (Matuszczak 1973). This field is currently one of the largest natural gas deposits known in the United States and allows producers to sell and transfer gas directly via pipeline to midstream companies, where it is processed and distributed to utilities and other purchasers. Like in other gas fields, however, there is no infrastructure to similarly transfer oil to markets directly via pipeline. Consequently, wells must be equipped with additional equipment to allow for the temporary storage and subsequent pick-up and transfer of their oil products by truck. We refer to these storage locations as batteries.

Noble Energy currently operates more than 7,500 wells with roughly 4,300 of such batteries in the Wattenberg field. These batteries, located near their respective wells, are spread out over a hundred mile radius in the DJ Basin. On a daily basis, the company must transport the produced oil from its batteries to several different purchasers and markets to meet its contractual sales obligations. These deliveries are performed by third-party trucking and hauling companies, which are currently assigned manually by dispatch personnel based on daily compiled priority lists. Anticipating a significant expansion of the oil production in the Wattenberg field in coming years, the work presented in this paper aims to assist both Noble Energy as well as other producers and operators with a flexible mathematical model to avoid potential inefficiencies and systematically represent such oil field operations for decision analysis, simulation, and optimization purposes. Specifically, we construct a multi-period, multiobjective mixed-integer program for the simultaneous optimization of revenue and sales, and the avoidance of temporary production shut-ins and sell-outs to guarantee long-term contractual obligations with partnering well owners, haulers, and markets. We also present a theoretical tradeoff analysis to validate our model decisions with current operational practice and demonstrate the use of this model in a small computational case study on an original data set provided by Noble Energy.

The remaining paper is structured as follows. Section 2 contains some further background information including an up-to-date review of related models and case studies in the recent literature. It then gives both an overview of some of the specific operations at Noble Energy and our resulting problem statement. We discuss our model decisions and formulation in Sect. 3 and present our theoretical tradeoff analysis between selected objectives in Sect. 4. Our computational case study is summarized in Sect. 5, and Sect. 6 concludes this paper with a few final remarks and an outline of possible further extensions of our work.

2 Background and problem statement

Production, transportation, and distribution planning and scheduling are classical problem domains of logistics and operations research that have been utilized in the oil and petroleum industries as early as the 1950s (Butler 1988; Garvin et al. 1957). While a large number of articles have been written in these areas and several handbooks have appeared on the general topics of transportation (Barnhart and Laporte 2006), supply chain management (de Kok and Graves 2003), and production and logistics (Graves et al. 1993), it is arguably out of scope for this contribution to give an accurate account of the wealth of literature available. Hence, we decided to limit the discussion in this paper to related articles mostly from the last few years; a more comprehensive bibliography of the reviewed literature with additional references is given in our preliminary report (Engau 2012).

Among the papers that we mention here, we highlight articles that propose new formulations or models, algorithms or methods, and applications or case studies. Similar to our present work, the recent papers by Neiro and Pinto (2004, 2005) and Rocha et al. (2009) describe new models for the planning and scheduling of oil production, delivery, and petroleum supply chains that can generally be formulated as large-scale, multi-period, mixed-integer linear or nonlinear programs. Considering cost minimization as a single optimization objective, however, these models were either more globally oriented or applied specifically to refinery operations at the energy company Petrobas.

To also incorporate multiple objectives, Lukac et al. (2008) present the interesting idea to generalize a traditional oil production–transportation model so that several producers can operate in multiple modes, which are characterized by different quantities and variable production costs. The formulation uses a bi-level, hierarchical decision structure in which the upper level organizes and minimizes costs from production to meet demands, and the lower level organizes and minimizes costs from transportation of the products to customers. The resulting problem is then solved as a dynamic program so as to minimize overall costs from both production and transportation. In comparison, however, the scope of our new paper is again more detailed in that we also include other than cost or profit-related criteria, which allows us to better understand and further analyze the tradeoffs between the different decisions and their resulting consequences.

In another approach using multiple objectives, De La Cruz et al. (2003) utilize a heuristic method from constraint evolutionary optimization to model the distribution of petroleum products through oil pipelines. Their objectives include the goal to deliver products on time, and to avoid consecutive shipments of products that may contaminate each other. Like in our case, limits in supply, transportation, and demand are included as additional constraints, but the focus to design a new evolutionary algorithm again is largely different from the purpose of our own paper.

More closely related to the problem of oil spills and motivated from the Deepwater Horizon incident in the Gulf of Mexico in 2010, Zhong and You (2011) address the optimal planning of oil spill response operations to minimize total cost and overall response time. Their model results in a bi-objective mixed-integer linear program to simultaneously predict the optimal time trajectories of oil volume and slick area, in addition to transportation profiles, resource utilization, cleanup schedules, and coastal protection. This paper nicely complements our own objective to ideally prevent such problems already in advance, by emphasizing environmental concerns and prominently integrating oil spill avoidance already in the planning of daily operations. Other papers that do not specifically address energy, gas, or oil distribution but more generally deal with the multi-objective design of transportation and routing networks are summarized in two annotated bibliographies by Current (1993) and Current and Min (1986), which together offer a large variety of other relevant criteria such as costs, revenues, profits, accessibilities, regional equity, and certain environmental concerns specific to the respective industries of interest in each of these different papers.

Again in the context of our own focus on oil load dispatch and transportation from multiple batteries to markets, we can highlight the recent study by Shen et al. (2011) who also deal with an inventory routing problem in which crude oil must be transported from a single port supply center to multiple customer harbors. Like in our case, the fleet of tankers must be rented from a third party and dispatched to satisfy demands over multiple periods, but due to the large number of oil-producing wells in our case, we must additionally consider the complication of dispatch from multiple locations. Additionally, and different from this and our own approach that can be solved as deterministic mixed-integer programs, other formulations also include stochastic aspects such as uncertain demands that must be remodeled or analyzed separately using techniques from stochastic optimization (Cao et al. 2010; Dempster et al. 2000; Leiras et al. 2010; MirHassani 2008; MirHassani and Noori 2011) or discrete-event simulations (Blouin et al. 2007; Cafaro et al. 2010; Cheng and Duran 2004; Ta et al. 2010; Tahar and Abduljabbar 2010).

For example, Kleywegt et al. (2002) consider a stochastic inventory routing problem that deals with the centralized coordination, replenishment, and transportation of inventory from a set of locations to a set of individual customers. Under the assumption that customers' daily demands are independent random vectors with a known probability distribution, the problem is formulated as a Markov decision process with an inventory state space and an action space that includes decisions regarding shipments, fleet assignments, and vehicle routings under constraints on both hauling and storage capacities. A distinct difference to our own model, however, is that in our case demands are typically known whereas it is primarily the production that may vary, or be shut in in the worst case. Hence, it appears that this in some sense inverse problem provides an interesting new variation also on other existing models that combine vehicle routing with inventory management and delivery scheduling, many of which are summarized in the recent survey article by Coelho et al. (2014). Finally, and specifically for dispatch problems formulated as mixed-integer programs, two older yet still insightful papers on solution techniques and formulations are those by Bixby and Lee (1998) and by Ronen (1995).

Like our own contribution, several of the former papers and some other authors also describe real-world applications or case studies with actual energy or petrochemical companies. Dating back to the 1980s, Klingman et al. (1987) describe an operational planning model for supply, distribution, and marketing of refined petroleum products that was implemented at Citgo, and Van Roy (1989) presents a solution to a multi-level production and distribution problem at an unnamed petrochemical company using network and transportation fleet optimization. The above paper by Bixby and Lee (1998) contains information about a case study with Texaco, conducted in the 1990s. Finally, the articles (Neiro and Pinto 2005; Rocha et al. 2009) by two different groups of authors highlight new model solutions developed more recently in the 2000s with Petrobras. Despite the basic similarities between all these related efforts, including our own model of the operations at Noble Energy, all these papers differ in significant detail by their mathematical representation and choices of known parameters, decision variables, and optimization criteria. To prepare the discussion of our own modeling choices, we continue in Sect. 2.1 with a slightly more detailed overview of our company's current dispatch and hauling operations which is then followed by our more specific problem statement in Sect. 2.2.

2.1 An overview of current operations

As already outlined in the introduction, in this paper we focus primarily on the dispatch, transportation, and distribution of Noble Energy's oil production in the DJ Basin's Wattenberg field. Produced from more than 7,500 wells, which cover an area of several ten thousand square miles, all gas and oil are first collected at about 4,300 different batteries. These batteries typically consist of a separator to divide gas and oil into separate streams, meters to measure the produced and transferred gas and oil products, a vapor recovery unit to capture evaporation from produced oil for reinjection into the gas line, a compressor to raise the pressure of the gas to exceed the pressure of the gas in the sales line, and one or more tanks that store the oil and any other liquid products, including both bottom sediment and water (BS&W) that subsequently separate from the lighter oil on top. Based on the flow rate of the produced oil within each battery, most batteries consist of one or two tanks with an average capacity of 300 barrels of oil (bbl) although there are also several batteries of higher capacity especially at recently opened, high-producing wells. In general, the flow rate at each battery shows only little variation but decreases exponentially over time.

Lease operators or pumpers are responsible for monitoring each battery, measuring and controlling oil levels and quality, grading BS&W content based on industry standards, and ultimately deciding whether to pump the oil for market delivery or to request haul for treatment at a separate facility or refinery. Based on the information provided by these individual pumpers, centralized dispatchers determine a multi-day service schedule of batteries to transport the produced oil to markets and meet sales obligations with well owners and purchasers. Service means that one or more trucks are sent to a battery to remove a truckload of oil (typically 180–200 bbl/load), and to deliver that oil to its designated destination. These deliveries are performed by third-party trucking and hauling companies, which may be assigned on a flexible basis as needed, based on mutual contracts, or a combination of both. After obtaining the battery inventory levels, the typical lead time for dispatching trucks varies to up to 36 hours, and service schedules are usually updated within a moving time window of at most three to four days. Although short-term adjustments of pick-ups and deliveries within this window are still possible, in principle, they are usually avoided due to their requirement of additional backup contracts with the partnering companies.

In current operations, all loads are delivered to three large markets (pipeline, railroad, and refinery) and several smaller, independent customers. Split loads, which occur when a single truck carries oil from two or more different batteries, are currently avoided because such loads are difficult to plan by dispatchers, create logistical overheads for pumpers and haulers, and could be rejected as being of uncertain quality by some markets. However, split loads are a natural way for risk pooling toward spills, by reducing inventory at multiple batteries rather than only a single location. This is important for the following reason. Due to the general uncertainties and variabilities involved in production and dispatch (e.g., production shortfalls at wells, mechanical failures at batteries, poor weather and delays of trucks, etc.), Noble Energy's on-hand inventory on any given day may currently be as high as 50 % of its total battery capacity. Hence, a major concern is that if all tanks at some battery become full or close to reaching capacity, the wells feeding into that battery are at risk of being "shut in" to prevent the tanks from overflowing. Such shut-ins are highly undesirable and expensive not only due to the additional logistics that is required to turn off and later reproduce a well, but also because of the potential violation of contracts with its owners and the resulting loss of general production. To prevent shut-ins and keep inventory at a sufficient but safe level, therefore, dispatchers currently compare battery capacities with available inventory or production levels and rates, which are used to compile priority lists according to which it is determined whether a battery needs to be serviced promptly, sometime soon, or not for a while. These priority lists, which are updated on a daily basis using additional information or specific requests from pumpers, currently form the main dispatch decision tool to determine the set of batteries that should be serviced during each following day.

2.2 Problem statement and objectives

The above description gives a basic understanding of the current dispatch and hauling operation that we decided to mathematically represent for further system analysis and optimization. Especially in view of the company's anticipated expansion, it was recognized that a manual process may lead to potential inefficiencies due to its high degree of complexity when different oil markets are competing and when the number of batteries and available trucking companies and trucks is either large or limited. Thus motivated, we were interested to formulate a model that could be used to more systematically analyze and decide on an efficient truck allocation for oil load dispatch and transportation planning of the produced oil from batteries to markets. While certain business agreements dictate who can haul from a particular battery to a particular market, we wanted to ensure that our model was flexible enough to also incorporate other and more general contractual agreements with well owners, haulers, and purchasers, and to take into account the risks of shut-ins as well as production or deliverability shortfalls. Optimal solutions using our approach should inform dispatchers about best decisions and strategies for haul and service dates of batteries, choices of haulers and markets, acceptance or rejection of split loads, avoidance of battery shut-ins, and optimal planning of inventory.

There are several frameworks that we could have chosen for our model, most generally including deterministic and probabilistic or stochastic optimization approaches. Among the latter, classical stochastic programming assumes that the problem is subject to uncertainties that are probabilistic and quantifiable using probability distributions or other statistical techniques (Birge and Louveaux 1997; Infanger 2011), whereas the more recent but already similarly well-established paradigm of robust optimization considers more general uncertainty sets without this assumption (Ben-Tal et al. 2009; Bertsimas et al. 2011). However, it was suggested that neither of these two approaches was truly necessary in our case for the reason that large demands were contractually guaranteed and variations in supply or production were relatively small during each sufficiently short but consistently overlapping planning period. Instead, to also include other than cost or profit-related criteria and thereby support a better understanding of any potential tradeoffs between different decisions and their resulting consequences, we agreed to use a model with multiple criteria that could be analyzed or solved using a wide variety of available goal, preemptive, or multi-objective programming techniques.

In discussions with Noble Energy, we then arrived at a total of four criteria that are used to evaluate the solutions of our model. Like the majority of other papers, we begin with a formulation including the single objective of profitability or cost minimization, which we express equivalently as maximization of revenue and subsequently utilize for the control of split loads. As highlighted in our former discussion, of particular importance also for preventing loss in revenue is the avoidance of shut-ins which we translated into the two related objectives to maximize sales or total haul, and the estimated time until batteries reach capacity by properly balancing inventory levels. The criterion to reliably ensure deliverability of guaranteed amounts and fulfill the sale, haul, and supply contracts with well owners, haulers, and purchasers is treated both as an optimization objective, by maximizing the days of available supply, and as a set of range constraints. Finally, while the company's primary concern of stewardship about its operations toward its stakeholders was not modeled explicitly, such considerations inform the high priority of shut-ins for spill avoidance and deliverability to business partners that are highlighted in our tradeoff analysis in Sects. 4 and 5.

3 Problem formulation and model

Our model formulation is based on a standard transportation-assignment problem in which we haul oil from a set B of batteries to a set D of destinations or markets. We denote the set of haulers or trucking companies by C, and we let the dispatch decision $x_{ijk} \geq 0$ be the amount of oil in barrels to be hauled from battery $i \in B$ using company $j \in C$ to market $k \in D$, for a known sales price or profit from sales of p_{ijk} dollars per barrel. The specific objectives and constraints of our model are described in the following subsections, and a nomenclature with a comprehensive list of sets, parameters, and variables used is summarized for convenience in Table 1.

3.1 Modeling contractual agreements

This first set of constraints ensures that our dispatch decisions satisfy contractual agreements and physical restrictions of batteries, haulers, and markets. We let l_i, l_j, and l_k be any guaranteed amounts of oil in barrels to be picked up from battery i, hauled using trucking company j, and delivered or sold to market destination k, respectively, and we use these three parameters in our model as lower bounds. The value of l_i is typically zero but included here to permit a nonzero lower bound, if desired. Similarly, we can include upper bounds v_i, u_j, and u_k to model total supply from battery i, haul capacity using trucking company j, and total demand of market k, respectively. The choice of the letter v rather than u for battery supply is on purpose as it will be generalized to a new inventory variable later (in Sect. 3.4).

$$\text{Battery constraints:} \quad l_i \leq \sum_{j \in C} \sum_{k \in D} x_{ijk} \leq v_i \quad \text{for all} \quad i \in B; \tag{1a}$$

$$\text{Hauling constraints:} \quad l_j \leq \sum_{i \in B} \sum_{k \in D} x_{ijk} \leq u_j \quad \text{for all} \quad j \in C; \tag{1b}$$

$$\text{Market constraints:} \quad l_k \leq \sum_{i \in B} \sum_{j \in C} x_{ijk} \leq u_k \quad \text{for all} \quad k \in D. \tag{1c}$$

3.2 Modeling load sizes and split loads

In practice, we typically dispatch a truck only when it can receive a full load, and we let h_{ijk} be the associated haul capacity of those trucks used by company j to deliver from battery i to market k in barrels (common sizes are 180 to 200 bbl/load). To restrict our dispatch decisions to full loads, we can introduce a new integer variable y_{ijk} that represents the number of loads that is sent from battery i via hauler j to market k.

Table 1 List of index sets, data parameters, and optimization variables

Sets		Indices
B	Set of batteries	i
C	Set of trucking companies or haulers	j
D	Set of destinations or markets	k
T	Set of time periods in planning horizon	t
$\mathcal{A}$	Collection of battery subsets admissible for split loads	$(A \subseteq B)$
Parameters		**Units**
h_{ijk}	Haul capacity per truck of hauler $j \in C$ from $i \in B$ to $k \in D$	bbl/load
h_{jk}	Haul capacity per truck of $j \in C$ to $k \in D$ (admissible for split loads)	bbl/load
p_{ijk}	Revenue or profit from selling a load hauled by $j \in C$ from $i \in B$ to $k \in D$	\$/load
q_{ijk}	Revenue reduction or split load cost of haul by $j \in C$ from $i \in B$ to $k \in D$	\$/load
l_i	Minimum contractual haul from battery $i \in B$ (typically zero)	bbl
l_j	Minimum contractual haul using trucking company $j \in C$	bbl
l_k	Minimum contractual supply to market $k \in D$	bbl
u_i	Maximum storage capacity of battery $i \in B$	bbl
u_j	Maximum haul capacity of hauler $j \in C$ per day	bbl
u_k	Maximum demand capacity of market $k \in D$ (possibly infinite)	bbl
r_i	Minimum reserve inventory to be kept in battery $i \in B$	bbl
v_i^0	Initial inventory at battery $i \in B$ at time $t = 0$	bbl
f_i^0	Initial oil flow at battery $i \in B$ at time $t = 0$	bbl/day
$f_i(t)$	Oil flow into battery $i \in B$ at time $t \in T$	bbl/day
λ_i/κ_i	Flow rate parameters at battery $i \in B$	–
Variables		
$s_i(t)$	Time until shut-in at battery $i \in B$ at time $t \in T$	days
$d_i(t)$	Time until sell-out / days of supply at battery $i \in B$ at time $t \in T$	days
$v_i(t)$	Ending inventory at battery $i \in B$ at time $t \in T$	bbl
$x_{ijk}(t)$	Barrels of oil hauled from $i \in B$ by hauler $j \in C$ to $k \in D$ at time $t \in T$	bbl
$x_i(t)$	Barrels of oil hauled from $i \in B$ at time $t \in T$ (required for split loads)	bbl
$y_{ijk}(t)$	Number of loads delivered from $i \in B$ by $j \in C$ to $k \in D$ at time $t \in T$	loads
$y_{jk}(t)$	Loads delivered by $j \in C$ to $k \in D$ at time $t \in T$ (required for split loads)	loads
$z_{ijk}(t)$	Approximate number of hauls from $i \in B$ by $j \in C$ to $k \in D$ at time $t \in T$	loads

$$\text{Full-load constraints (no split loads): } x_{ijk} = h_{ijk} y_{ijk} \text{ and } y_{ijk} \geq 0 \text{ integer.} \quad (2)$$

On occasion, however, it is also possible that a single truck is sent to multiple batteries to only receive partial loads that together give a full load. For this case, we define a collection $\mathcal{A}$ of subsets $A \subseteq B$ that contain those batteries that can be serviced by the same trucking company j along a single route to market k, with trucks of capacity h_{jk} bbl/load. We then let the haul capacity h_{jk} be independent of a specific battery and modify constraints (2) to also allow for such split loads from multiple batteries.

$$\text{Full-load constraints (with split loads): } \sum_{i\in A} x_{ijk} = h_{jk}y_{jk} \text{ and } y_{jk} \geq 0 \text{ integer.} \quad (3)$$

The integer variable $y_{jk} \geq 0$ now represents the number of deliveries to market k using trucking company j. In particular, by choosing $\mathcal{A} = B$, we could allow split loads from any set of batteries.

3.3 Modeling split load penalties and profit

Although split loads provide additional flexibility and may increase the amount of total haul, they typically create additional costs for trucking companies that are returned to operators and thus must be accounted for when computing profit. For that purpose, we introduce a new set of integer variables z_{ijk} and a new set of constraints:

$$x_{ijk} \leq h_{jk}z_{ijk} \text{ and } z_{ijk} \text{ integer.} \quad (4)$$

For a given dispatch decision x_{ijk}, the smallest feasible value of z_{ijk} now corresponds to a lower bound on the number of trucks of company j that need to be sent from battery i to market k. The number of split loads is thus at least as large as the difference between this value and the actual deliveries y_{jk}, which reduces the revenue or profit term with a penalty factor q_{ijk} that generally depends on battery i, hauler j, and market k. This yields an adjusted revenue or profit from sales:

$$\sum_{j\in C}\sum_{k\in D}\left(\sum_{i\in B} p_{ijk}x_{ijk} - q_{ijk}\left(\sum_{i\in B} z_{ijk} - y_{jk}\right)\right) = \sum_{i\in B}\sum_{j\in C}\sum_{k\in D}\left(\left(p_{ijk} + \frac{q_{ijk}}{h_{jk}}\right)x_{ijk} - q_{ijk}z_{ijk}\right), \quad (5)$$

where we used Eq. (3) to express the variables y_{jk} in terms of x_{ijk}. Maximization of (5) guarantees that z_{ijk} will take on the smallest value that makes constraint (4) feasible, so that this variable corresponds to the desired ceiling value $z_{ijk} = \lceil x_{ijk}/h_{jk} \rceil$ for a minimum number of split loads. To prevent split loads completely, we can either set q_{ijk} to a very large value or again simplify the model by choosing (2) instead of (3), then removing the variables z_{ijk} with its associated constraints (4) and penalty terms in the objective function (5).

It should be noted that this modeling technique does not provide the exact number of split loads, which would require to integrate an additional bin-packing optimization subproblem into the above model. For example, using trucks with capacities of 180 barrels each to haul from three batteries with current inventories of 300 barrels each, the above model would indicate only six hauls although we would require at least seven hauls to receive five full loads. To see why this is, first suppose that we are sending three trucks for one full (non-split) load to each of these three batteries. This would leave 120 barrels at every battery and require two more trucks to pick up from two batteries each for another four hauls, with a resulting total of at least seven hauls. Due to the combinatorial nature of computing the exact number of minimum total hauls, however, and for simplicity and model tractability, therefore, we have chosen the former, simpler approach.

Finally, several other requirements can be incorporated either by adding further constraints, or by setting suitable sales prices p_{ijk}. For example, if a certain battery i or market k must (or cannot) be serviced by a certain trucking company j, we could introduce additional constraints to prescribe or prevent a corresponding assignment, or alternatively set the corresponding profit p_{ijk} to a large positive (or negative) value.

3.4 Modeling oil inventory and flow rates

In constraint (1a), we assumed a constant value v_i for the total supply at each battery i to temporarily simplify the explanation of our model. Realistically, however, the available supply changes over time and depends both on the production and flow of oil into the battery, and the amount of oil that is previously hauled. Hence, we model the oil inventory $v_i(t)$ at each battery i using a difference equation over a planning period T with discrete time steps t (typically days):

$$v_i(t) = v_i(t-1) + f_i(t) - x_i(t) \text{ with } x_i(t) = \sum_{j \in C} \sum_{k \in D} x_{ijk}(t) \tag{6}$$

where $f_i(t)$ denotes the (generally unknown) oil flow into battery i at time t in barrels (per day), and the dispatch decisions $x_{ijk}(t)$ may now also vary over time (with the same unit of bbl/day). Industry experience shows that the flow rates that determine $f_i(t)$ vary monotonically and typically decrease flow exponentially as $f_i(t+1) = (1-\kappa_i)f_i(t)$ for some flow battery-dependent constant κ_i that can be estimated from historical data:

$$f_i(t) = f_i^0 e^{\lambda_i t} \text{ with } \lambda_i = \ln(1-\kappa_i), \tag{7}$$

where $f_i^0 = f_i(0)$ is the measured flow rate into battery i at time $t = 0$. Extending all relevant constraints and other variables to the planning period T we now replace v_i by $v_i(t)$ in (1a), and we let r_i and u_i be an optional minimal reserve inventory to be kept at battery i and its maximum capacity, respectively. The resulting multi-period optimization model is given below.

$$\underset{x,y,z,v}{\text{Maximize}} \sum_{i \in B} \sum_{j \in C} \sum_{k \in D} \sum_{t \in T} \left(\left(p_{ijk} + \frac{q_{ijk}}{h_{jk}} \right) x_{ijk}(t) - q_{ijk} z_{ijk}(t) \right) \tag{8a}$$

$$\text{subject to } l_j \leq \sum_{i \in B} \sum_{k \in D} x_{ijk}(t) \leq u_j \text{ for all } j \in C \text{ and } t \in T; \tag{8b}$$

$$l_k \leq \sum_{i \in B} \sum_{j \in C} x_{ijk}(t) \leq u_k \text{ for all } k \in D \text{ and } t \in T; \tag{8c}$$

$$l_i \leq \sum_{j \in C} \sum_{k \in D} x_{ijk}(t) = f_i(t) - v_i(t) + v_i(t-1) \text{ for all } \; i \in B \text{ and } t \in T; \tag{8d}$$

$$r_i \leq v_i(t) \leq u_i \text{ and } v_i(0) = v_i^0 \text{ for all } i \in B \text{ and } t \in T; \tag{8e}$$

$$\sum_{i \in A} x_{ijk}(t) = h_{jk} y_{jk}(t) \text{ and } 0 \leq x_{ijk}(t) \leq h_{jk} z_{ijk}(t) \text{ for all } A \in \mathcal{A} \text{ and } i, j, k, t; \tag{8f}$$

$$y_{jk}(t) \geq 0 \text{ and } z_{ijk}(t) \geq 0 \, \text{integer}. \tag{8g}$$

This results in a model with $|B| \cdot |C| \cdot |D| \cdot |T|$ linear variables, $(|B|+1) \cdot |C| \cdot |D| \cdot |T|$ integer variables, and $2 \cdot (2 \cdot |B| + |C| + |D|) \cdot |T| + (|\mathcal{A}| + |B|) \cdot |C| \cdot |D| \cdot |T| + |B|$ equality or inequality constraints.

Of course, all lower and upper bounds l_i, l_j, l_k and u_i, u_j, u_k, the minimum inventory levels r_i, the trucking capacities h_{jk}, and the sales prices p_{ijk} can also be made time-dependent without further increase in the size of the model, if necessary. For example, certain trucking companies may not haul or certain markets may not accept deliveries on certain (weekend) days, or vary in availabilities, prices, or costs.

3.5 Model discussion and additional objectives

Thus far, our model formulation (8) allows us to produce an optimal dispatch schedule for a planning period T to maximize revenue or profit from sales subject to given contractual obligations and physical specifications of batteries, haulers, and markets. Specifically, our dispatch decisions $x_{ijk}(t)$ suggest the amount of oil to be hauled at time t (typically a certain day) from battery i to market k using trucking company j. The dependent auxiliary variables $y_{jk}(t)$ correspond to the number of full loads that a certain company j delivers to market k at time t, whereas the variables $z_{ijk}(t)$ also include an approximate count (lower bound) of the corresponding number of split loads at each battery i. The oil inventory variables $v_i(t)$ that connect the different time periods follow directly from our dispatch decisions and equations (6) and (8d-8e). Finally, the choice of a finite rather than infinite time interval T agrees with common operational practice: in response to control measurements of predicted oil production and inventory and to accommodate any changes or new requests of contracts, the data set must frequently be updated and long-term schedules are usually of little relevance for weekly or daily operations. Unlike for strategic planning, therefore, the above model is solved repeatedly for overlapping planning periods and in much shorter time intervals to achieve continuity by regularly comparing and adjusting the mathematical model based on actual, current operations.

While our model is focused primarily on operational dispatch, however, it is important to also address strategic business decisions including the negotiation of the guaranteed minimum amounts l_j and l_k with haulers and markets, respectively. In particular, it appears that we would yield maximum profit if $l_j = l_k = 0$ as there would be no more obligations to fulfill that could constrain an otherwise optimal dispatch strategy, but this reasoning ignores that the sales prices p_{ijk} are also an immediate consequence of such negotiations and could be significantly smaller without any contractual guarantees. Similarly, while our model seems to ignore travel times and distances between batteries and markets that impact the operation of our partnering haulers and thus shape external costs for trucking the oil, such considerations are assumed to be included implicitly as bounds on overall haul capacities and costs or revenue deductions when pricing the profit terms p_{ijk}.

In view of the company's internal operations, another interesting question is the choice of the minimum reserve levels r_i in constraints (8e). From a mathematical or management perspective, it is again true that no inventory is optimal as it provides the most flexibility in choosing an optimal dispatch strategy. From an operational point of view, however, a positive inventory is crucial because of the general uncertainties and variabilities in oil production and market demand. For example, a well could unexpectedly begin to produce less oil than expected, and bad weather in the field or mechanical failures of the pumping equipment could cause a loss in production and a subsequent shortfall in needed supply. For such reasons, we expect to keep a significant percentage of total capacity as on-hand inventory.

Although a positive inventory guarantees deliverability in times of production shortfalls, it also increases the risk of shut-ins in times of unforeseen changes in hauling capacities or market demand. For example, transportation delays, truck failures, demand deficiencies, or an unexpected increase in oil production may cause certain batteries to fill up more quickly than expected and reach capacity before a truck can be dispatched to haul its oil. Hence, to prevent such a situation we are generally interested to maximize sales or haul from quickly filling batteries to maintain an inventory level well below their overall capacity. Our model and analysis of the resulting tradeoff between the maximization of revenue and these additional objectives—maximization of sales and total haul, avoidance of shut-ins, and guaranteed deliverability in the case of unexpected production changes—is discussed in more detail in the remaining sections of this paper.

4 Tradeoff analysis of shut-in avoidance and deliverability

Model formulation (8) so far considers only the maximization of revenue or profit. Based on our model discussion, however, we will also consider additional criteria to ensure that our dispatch schedule is robust toward variabilities in oil production, transportation, and supply. Specifically, we now extend our initial model by three additional objectives to ultimately balance the maximization of revenue or profit with sales or total haul, avoidance of shut-ins, and guaranteed deliverability.

4.1 Modeling and asymptotic analysis of sales and total haul

We model the maximization of sales and total hauls analogously to the maximization of profit or revenue in (5) and (8a) in which we simply drop the associated prices and penalty terms:

$$\text{Total Haul: Maximize } \sum_{i\in B}\sum_{j\in C}\sum_{k\in D}\sum_{t\in T} x_{ijk}(t) = \sum_{i\in B}\sum_{t\in T} x_i(t), \tag{9}$$

where $x_i(t)$ denotes the planned amount of oil to be sold and hauled from battery i. Under this objective, we expect a relatively constant amount of inventory $v_i(t)$ close to its set reserved level r_i in the inventory Eqs. (6) and (8d). If inventory is constant, this also suggests that the haul amount $x_i(t)$ from battery i closely corresponds to its projected production or flow rate $f_i(t)$ to keep a constant inventory between reserve levels r_i and battery capacity u_i:

$$r_i \le v_i(t) = v_i(t-1) + f_i(t) - x_i(t) \le u_i \quad \text{for all } i \in B. \tag{10}$$

However, due to load size requirements and based on split load policies, this does not necessarily imply that $x_i(t)$ and $f_i(t)$ are identical for all $i \in B$ and $t \in T$; for example, a well with a low flow rate may produce multiple days or weeks without haul while building up inventory, and a truck may be dispatched only once the battery can actually provide a full load. Therefore, we would only expect that optimal dispatch $x_i(t)$ and inventory $v_i(t)$ resemble periodic steady-state solutions that successively decrease in value due to the expected decrease of oil production at each well over time. In particular, over the full life time of each battery and upon full depletion of its corresponding wells, we know that

$$\lim_{|T|\to\infty} \sum_{t\in T} x_i(t) = \lim_{|T|\to\infty} \sum_{t\in T} f_i(t). \tag{11}$$

From a business perspective, we must plan for the depletion of current wells either by negotiating new contracts with smaller amounts to continuously meet contractual obligations, or by opening new wells and batteries to again increase total oil production. Without consideration of contract negotiations and the opening of new wells, however, this suggests that the maximization of sales or haul may not have a major impact on operational dispatch and lead to service schedules that agree with the maximization of revenue. This assertion is confirmed in our later computational results.

4.2 Modeling of shut-in avoidance and deliverability

In view of the resulting inventory levels $v_i(t)$ that follow as a direct consequence from our dispatch decisions $x_{ijk}(t)$, our primary concerns are unforeseen variabilities in production and transportation that increase our risks of shut-ins and contract violations due to inventory sell-outs, respectively. The shut-in of a well occurs if our former model becomes infeasible due to one or more batteries reaching capacity in constraint (8e). We quantify the associated risk by the time until shut-in $s_i(t)$, which is modeled as the difference in battery capacity u_i and current inventory $v_i(t)$ divided by the expected flow rate $f_i(t)$:

$$s_i(t) = \frac{u_i - v_i(t)}{f_i(t)}. \tag{12}$$

This value is merely an approximation for the actual time until shut-in because the flow rates $f_i(t)$ may also change and generally decrease over time; in that case, our measure is conservative and underestimates the actual value which adds additional robustness to the solution of our model.

Similarly, we quantify the risk of violating contractual agreements due to production shortfalls by the current time until inventory sell-out, which is modeled as the days of supply $d_i(t)$ corresponding to the length of time we could continue to meet planned dispatch $x_i(t)$ using the currently available inventory levels $v_i(t)$:

$$d_i(t) = \frac{v_i(t)}{x_i(t)}. \tag{13}$$

Our objective in both cases is to minimize these risks which is equivalent to the maximization of $s_i(t)$ and $d_i(t)$, respectively. The resulting multicriteria optimization model can be formulated as follows and remains subject to the same constraints as model (8):

$$\underset{x,y,z,v}{\text{Maximize}} \left\{ \sum_{i \in B} \sum_{j \in C} \sum_{k \in D} \sum_{t \in T} \left(\left(p_{ijk} + \frac{q_{ijk}}{h_{jk}} \right) x_{ijk}(t) - q_{ijk} z_{ijk}(t) \right), \right. \tag{14a}$$

$$\left. \sum_{i \in B} \sum_{t \in T} x_i(t), \text{ and } s_i(t) \text{ and } d_i(t) \text{ for all } i \in B \text{ and } t \in T \right\}. \tag{14b}$$

4.3 Model discussion and tradeoff analysis

To deal with the multiple objectives in our final model (14), we can use one of several methods from multiobjective programming or multicriteria decision-making (Ehrgott and Gandibleux 2002; Figueira et al. 2005). It is well-known that in the presence of multiple and typically conflicting criteria, a unique best solution does not usually exist so that a decision-maker—or dispatcher in our case—must choose from a set of efficient, Pareto optimal solutions to weigh and compromise the different objectives. There are many techniques that can support this decision-making process, so that we refrain from recommending a single method to "solve" the above problem. Instead, we only outline some of the more popular techniques and for illustration describe one of the general approaches that we studied together with Noble Energy.

One of the more common techniques especially for linear and convex formulations is to aggregate all objectives as a single weighted sum and thus reduce the multicriteria problem to one with a single objective. For example, we already used this approach implicitly in objective (5) where we combined revenues and costs using profit weights p_{ijk}, and quantified implicitly the tradeoff between the costs and potential increases in profit from split loads using the penalty factors q_{ijk}. Although the choice of suitable weights to properly reflect desirable tradeoffs is often quite difficult, and despite the well-known fact that this method is not generally suitable to find good tradeoffs when the set of realizable solutions is not convex, a full or partial aggregation of all or some criteria is convenient especially if different criteria are largely concurrent or measured in comparable units. For example, it could be reasonable to aggregate or average shut-in and sell-out risks over time; moreover, if a dispatcher can identify batteries at which shut-ins or production shortfalls are more or less acceptable, one could also use corresponding priorities w_i for a weighted aggregate or average of each risk over all batteries:

$$\text{Maximize} \sum_{i\in B} \sum_{t\in T} w_i s_i(t) \text{ and } \sum_{i\in B} \sum_{t\in T} w_i d_i(t). \tag{15}$$

The priority weights w_i, which could also be different for $s_i(t)$ and $d_i(t)$ or normalized if necessary, are best chosen so that greater values are assigned to high-priority batteries at which shut-ins must be avoided, and smaller values are given to batteries that are of less concern.

For problems that are not convex, which is often the case for mixed-integer programs, a better alternative to weighted sums are weighted distance functions or certain (modified or augmented) Tchebycheff norms. Hence, for the computational results in this paper specifically we used a related max-min technique that is particularly robust if all risks are considered to be of equally high importance so that tradeoffs against or in favor of certain batteries are not acceptable. In this case, we can formulate the two new objectives $\max\min\{s_i(t) : i \in B \text{ and } t \in T\}$ and $\max\min\{d_i(t) : i \in B \text{ and } t \in T\}$ that maximize the minimum times until shut-in and sell-out over all batteries and planning days to yield the overall smallest risk possible:

$$\begin{aligned} &\text{Maximize}\, s \text{ and } d \\ &\text{subject to}\, s \le s_i(t) \text{ and } d \le d_i(t) \text{ for all } i \in B \text{ and } t \in T. \end{aligned} \tag{16}$$

This reduces problem (14) to a four-criteria problem with one objective each for the maximization of profit and revenue, sales and total haul, avoidance of shut-ins, and guaranteed deliverability. Alternatively, and based on additional information on which batteries are situated close to each other (e.g., similar to the collection $\mathcal{A}$ of subsets of batteries that are admissible for split loads), one could also assign groups of batteries to clusters that may further mitigate the associated risks from shut-ins or sell-outs, respectively.

As we already discussed in Sect. 4 and quite typical for multiobjective programs with more than two criteria, it is often possible to analyze tradeoffs in smaller subproblems with only two decision criteria (Engau 2009; Engau and Wiecek 2007). For example, for the model above we expected and could computationally confirm that the first three objectives are not in major conflict and similarly favor to sell large amounts (maximization of sales) in an efficient manner (maximization of profit) while keeping oil inventory low - or ideally at zero - to avoid the shut-in of wells. Despite this apparent concurrence between these objectives, however, as part of our computational experiments we later discuss that there still exists a hidden tradeoff that stems from the allowance or rejection of split loads based on the chosen split load penalty. In addition, the guarantee of deliverability conflicts with especially the first and third of these goals: the maximization of sales may require the commitment to higher contractual obligations, which may necessitate to hold more reserve inventory that thereby also increases the risk of subsequent shut-ins. Of course, the decision and negotiation of contracts is beyond the operational level and thus not included in our tradeoff analysis.

Hence, in our remaining discussion we now focus on the most important tradeoff between the avoidance of shut-ins and guaranteed deliverability, motivating no or full inventory, respectively. In particular, using the same min-max strategy as in (16) but applied to each pair of shut-in and sell-out times $s_i(t)$ and $d_i(t)$, it is not difficult to see that the most conservative decision would be to perfectly balance these risks at each battery so that $s_i(t) = d_i(t)$ for all $i \in B$, or equivalently:

$$\frac{u_i - v_i(t)}{f_i(t)} = \frac{v_i(t)}{x_i(t)} \quad \Longrightarrow \quad v_i(t) = \frac{x_i(t)u_i}{x_i(t) + f_i(t)}. \tag{17}$$

Using (11), this allows us to compute the average inventory that should be kept under this strategy:

$$\lim_{|T|\to\infty} \sum_{t\in T} \frac{v_{i(t)}}{|T|} = \lim_{|T|\to\infty} \sum_{t\in T} \frac{x_i(t)u_i}{(x_i(t) + f_i(t))|T|} = \frac{u_i}{2} \tag{18}$$

This asymptotic tradeoff result agrees with Noble Energy's current operational practice to keep up to 50 % of its capacity as on-hand inventory and thus validates some of our basic modeling decisions.

5 Model implementation and computational case study

For our computational case study, we implemented our model using the mathematical programming modeling language GAMS and solved all resulting optimization problem instances using IBM/ILOG's CPLEX 12.3 on a Quad Core Opteron 2.0 Ghz processor with 64GB RAM. The underlying data was provided by Noble Energy and includes battery capacities with historical production and inventory levels, minimum and maximum agreements with haulers and their corresponding truck sizes, and guaranteed sales to markets with applicable supply and transportation costs. The battery data consists of over 3,400 locations and thus represents about 80 % of the company's total dispatch operation in the Wattenberg field. The historical production data at each battery included inventory measurements at irregular intervals over a few months or days for longer-producing or newly-opened wells, respectively, which were used to fit functions of the form (7) and accordingly predict their flow rates in the future. Figure 1 gives several histograms that summarize the distributions of battery capacities u_i, relative inventories v_i^0/u_i, current production rates f_i^0, and estimated (shortest) times until shut-in (TSI) $s_i^0 = (u_i - v_i^0)/f_i^0$ at the beginning of our study. The vertical axis in each case gives frequency in percent.

These histograms indicate that about 75–80 % of all batteries have a single tank with a capacity of 300–400 bbl, with almost all of the remaining batteries below 800 bbl. The relative inventory levels in percent of total capacity for each battery vary between 0 and 90 % with an average of 41 %. The total current inventory is 497,476 bbl compared to a total capacity of 1,358,991 bbl, providing a relative inventory of 37 % overall. The production rates vary widely between less than 1 bbl/day and up to over 1,000 bbl/day, with an average of 8.5 bbl/day and less than 1 % of all batteries receiving 100 bbl/day or more. The total daily production of these batteries is 28,914 bbl.

The TSI among all batteries are similarly widely spread, with a minimum of 8 hours for the fastest filling batteries, an average of 6 months, and a maximum of several hundred years for several low-producing batteries. The corresponding histograms give an idea of the percentage of batteries whose TSI falls within a year, a quarter, or the next two weeks. For example, the first and second of these plots show that about one third of all batteries have shut-in times of less than a month, with the quarter's peak at about four weeks for 10 % of all batteries. Limited to a period of two weeks as seen on the third plot, a little below 1 % of all batteries have shut-in times of four days or less, still corresponding to more than 30 batteries that need to be serviced with highest priority.

Hence, to reflect actual operations in practice, for our computational analysis we reduced the full data set to only those batteries with a currently short TSI, including all batteries that were very close to capacity (even if their flow rate was relatively small) or that received oil with a very large flow rate (even if their current inventory level was still low). Specifically, we included all of those batteries with either an estimated TSI within the next 4 days, a current inventory level of at least 90 %, or an initial flow of 180 bbl or more per day. This resulted in a subset of 34 batteries to represent about 1 % of the full data set available, but including all those batteries of highest priority for dispatch. Figure 2 shows the characteristics of this data set and includes capacities and inventories (trimmed at 16,000 bbl for the largest batteries), flow rates and estimated TSI for all 34 selected batteries. The used data in comparison to the full data set, and the correspondingly scaled amounts for hauls and supplies are summarized as aggregated totals in Tables 2 and 3.

In view of Table 3, it is clear that the lower bound on market supply is dominated by the minimum contracted hauls, and that the practically infinite market demand is restricted by the maximum available hauling capacity. Because the total flow of all batteries falls in between these lower and upper bounds, we can expect our model to be feasible over a sufficiently short time period, in which daily production is not reduced by too much. Specifically, based on the available flow profiles provided by the company, the computed flow rate parameters λ_i in (7) were in the order of 0.01 and thus small enough to justify the assumption of a constant daily production.

5.1 Maximization of revenue, total haul, and time until shut-in

Using the above data sets, we first look at the results when solving model (8) for maximum revenue or profit, over a two-week period. For the revenue computation, oil prices were estimated at \$103.15/bbl to correspond to the average WTI crude oil price index for the first quarter in 2012, and adjusted by TSH (transportation,

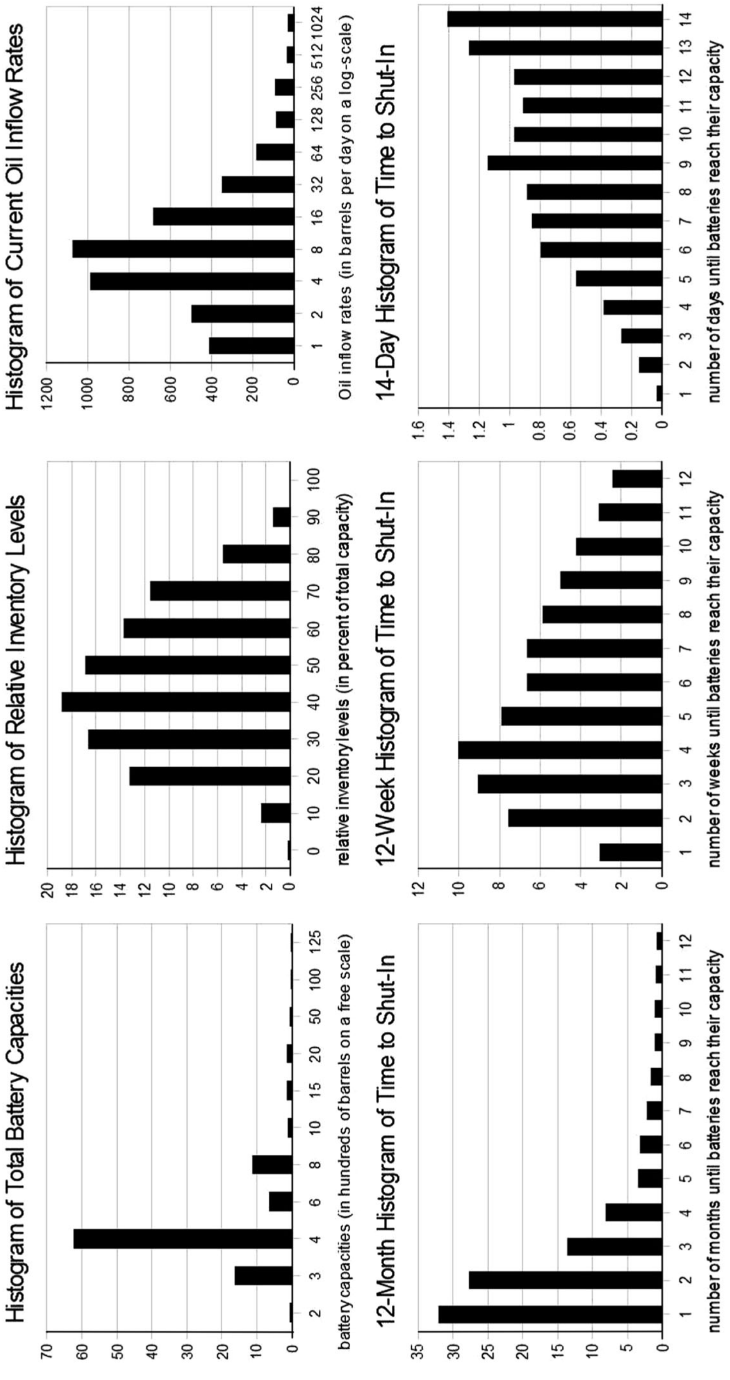

Fig. 1 Histograms of battery specifications and shut-in times

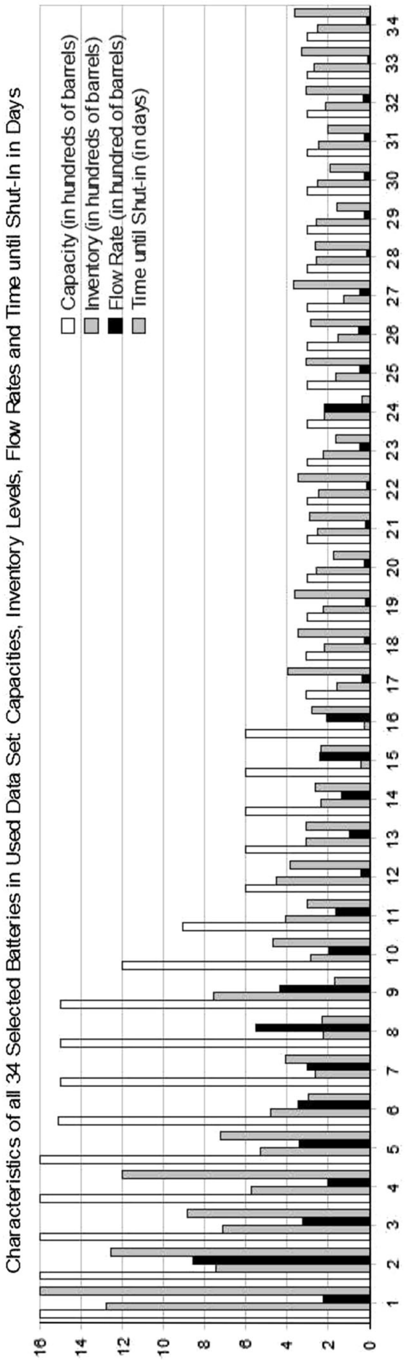

Fig. 2 Characteristics of the 34 Batteries Included in Used Data Set

Table 2 Aggregated totals of battery data in full and used data sets (in barrels)

	Batteries	Inventory	Capacity	(Rel inv) (%)	Flow rate	Avg TSI
Full data set	3,406	497,476	1,358,991	(37)	28,914	193.66
Used data set	34	11,321	49,719	(23)	5,369	4.09
Percentage (%)	1	2	4		19	

Table 3 Aggregated totals of truck and market data in full and used data sets

	Haulers	Min haul	Max haul	Markets	Min supply	Max supply
Full data set	6	19,800	57,240	5	15,300	Infinite
Used data set	6	3,780	10,980	5	2,880	Infinite
Percentage (%)	100	19	19	100	19	

shipment, and handling) fees provided by Noble Energy for the respective hauls to markets. The resulting model was solved three times: first to prevent any split loads with a large penalty term, and second to allow split loads with a penalty value computed as $q_{ijk} = p_{ijk}h_{ijk}/4$. This choice implies that each split load reduces profit from that load by 25 %. Third, for comparison we also computed the maximum (ideal) revenue with split loads but no penalties, by setting $q_{ijk} = 0$. Problem sizes and running times are reported in Tables 4 and 5, and the resulting optimal revenues with their corresponding amounts of haul and average and minimum times until shut-in (TSI) and sell-out (TSO) are listed in Table 6. In Table 4, the slightly larger numbers of variables and constraints in our computational GAMS model compared to its algebraic formulation (8) follows from our use of several auxiliary variables for ease of model implementation.

The solution statistics in Table 5 indicate that the choice of split load penalty has a significant impact on the required number of iterations and overall solution time. Whereas the problem solves relatively quickly for small or no penalties also for an increasing number of batteries, the poor algorithmic performance when choosing a large penalty is partially due to the difficulty in finding an initial feasible solution but primarily due to numeric difficulties, which of course could be avoided by removing any split load variables and penalties from the model, if desired. Moreover, the results in Table 6 clearly illustrate that both revenue and total haul increase if we allow split loads at a penalty, or for free. In particular, we found that the maximum values of $7,454,030 (or $7,693,380) for revenue and 78,480 (or 81,000) bbl for total haul also coincide with the corresponding single-objective ideal values, indicating that there is no direct tradeoff between these two concurrent objectives as they can reach their best values simultaneously. Because the haul objective does not depend on the split load penalties and thus may be as high as 81,000 bbl also for the solution in the second row of Table 6, this shows that there must exist a hidden tradeoff that stems from the rejection of certain split loads at this chosen penalty. Specifically, to further quantify this tradeoff we found that a split load penalty of more than 33 % revenue results in no more split loads and thus

Table 4 Problem sizes for instance $|B| = 34$, $|C| = 6$, $|D| = 5$, $|T| = 14$, and $|\mathcal{A}| = 1$ ($\mathcal{A} = \{B\}$)

Computational model (GAMS)				Algebraic model formulation (8)		
Linear vars	Integer vars	Constraints	Non-zeros	Linear vars	Integer vars	Constraints
15,713	14,700	18,819	177,462	14,280	14,700	16,946

Reduced MIP model (after probing/presolve)				Reduced LP model (after presolve)		
Linear vars	Integer vars	Constraints	Non-zeros	Linear vars	Constraints	Non-zeros
14,785	14,670	15,414	101,297	14,755	1,134	72,317

Table 5 Iterations, nodes, cuts, solution times for root and branch-and-cut, and final gap

Split loads	Penalty	Iterations	Nodes	Cuts	Root (s)	B&C (s)	Total (s)	Gap (%)
No	Large	134,998	18,494	1,371	10.31	899.77	910.07	9.66
Yes	Small	4,500	440	736	13.82	20.77	34.59	5.28
Yes	None	2,155	0	382	0.00	3.58	3.58	0.11

Table 6 Optimal objective values for revenue maximization over a two-week period

Split loads	Penalty	Revenue	Total haul	Avg TSI	Min TSI	Avg TSO	Min TSO
No	Large	7,454,030	78,480	7.77	0	4.62	0
Yes	Small	7,533,704	79,560	7.31	0	5.08	0
Yes	None	7,693,380	81,000	8.02	0	4.37	0

matches the optimal solution using full loads only, in the first row of Table 6, whereas a split load penalty of less than 13 % always yields the maximum haul of 81,000 bbl.

To visualize the dispatch schedules and gain some additional insight about the corresponding inventories over the selected two-week planning period, we can study the corresponding inventory profiles. Depicted in Fig. 3 for a typical high-flow five-tank and mid-flow single-tank battery (batteries 8 and 31 in Fig. 2), the first and second plot show the respective development of their inventory, the flow of oil into each battery, and the haul out of it. For example, for the single-tank battery with a 300 bbl capacity and an initial inventory and flow of 245 bbl and 28 bbl/day, respectively, we see that we dispatch a single truck at time periods 1, 6, and 13 to keep inventory roughly between 50 and 200 bbl, or 17 and 67 % of total capacity. The situation is more complex for the larger battery with 1,500 bbl capacity and an initial inventory and flow of about 225 and 554 bbl/day. Because this battery tends to reach capacity every three days, the optimal solution indicates a much more irregular dispatch schedule and tends to keep a higher (relative) inventory between 300 bbl (20 %) and full capacity (100 %). In particular, days at which the battery reaches full capacity are followed by days at which it is serviced up to nine times, for a total haul of over 1,600 bbl including its full-capacity inventory in addition to parts of its same-day production.

Especially the third plot in Fig. 3 also indicates that the computed dispatch schedules tend to clear inventory toward the end of the fixed planning period, to collect maximum additional revenue as the model does not impose any other constraints to be satisfied in later periods. By periodically updating the model and purposely running it for a slightly longer period than planned, however, such tendencies will usually not impact operational dispatch whose planning periods are typically no longer than 3 or 4 days. In particular, the initial priority list of batteries to be included in such a model should be updated at least as often as their average time until shut-in or sell-out, which equals about 4–5 days for the solutions in Table 6. Without explicit consideration of TSI and TSO as optimization objectives, however, their minimum values must be expected to be zero in general as especially high-flow batteries like the one in Fig. 3 may reach capacity and haul full-capacity inventory, which necessarily implies that both of these times in the following periods are zero. This is again confirmed by the results in Table 6.

Hence, to analyze some of the other concurrence or tradeoff relationships between the maximization of revenue or haul, and the times to shut-in or sell-out, we also computed the single-objective ideal values when maximizing the minimum TSI or TSO alone. The respective maximum values that we obtained with split loads were 1.38 and 1.13 days for TSI and TSO, respectively, and the same rounded value of 0.62 days if split loads were not allowed. We then formed an aggregated objective function to maximize all four objectives simultaneously, and found a new solution that produced maximum (ideal) values for revenue ($7,693,380), total haul (81,000 bbl), and TSI (1.38 days), and average TSI and TSO of 8.43 and 3.96 days, respectively. This shows that again there is no tradeoff between maximization of revenue, haul and TSI when allowing unrestricted split loads, as all objectives can reach their best values simultaneously. The corresponding inventory profiles for the same two batteries as in Fig. 3 are depicted in Fig. 4 and confirm our expectation that when maximizing TSI without tradeoff consideration to TSO, optimal dispatch tends to clear out inventory at high-flowing batteries and thereafter match hauls to the battery's daily production.

5.2 Discussion of tradeoff between times until shut-in and sell-out

To conclude this brief discussion of our selected computational results, we lastly consider the tradeoff between times until shut-in (TSI) and sell-out (TSO), or equivalently, the tradeoff between avoidance of shut-ins and deliverability that we analyzed theoretically in Sect. 4. From our previous results, we have observed that revenue or profit, sales or total hauls, and TSI can be maximized simultaneously if split loads are allowed, and give rise to only a relatively small tradeoff if split loads are forbidden or penalized. In addition, we have also already mentioned that without split loads TSI and TSO attain the same maximum value of 0.62 days, whereas their optimum (ideal) values with split loads are roughly twice as high at 1.38 and 1.13 days, respectively.

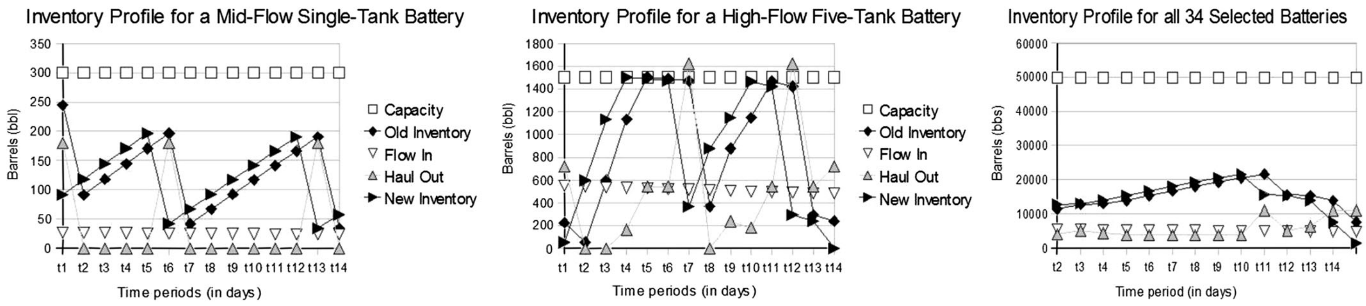

Fig. 3 Inventory profiles for batteries when maximizing revenue and total hauls

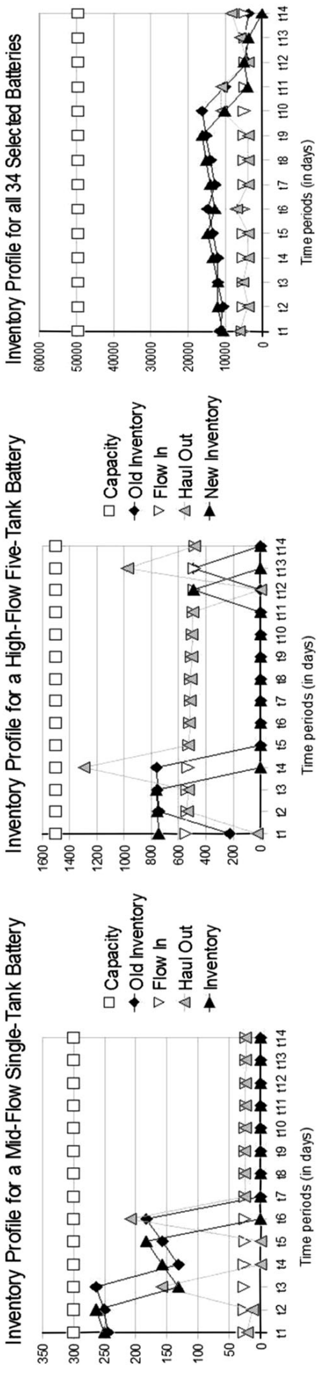

Fig. 4 Inventory profiles for batteries using maximization of revenue and times until shut-in

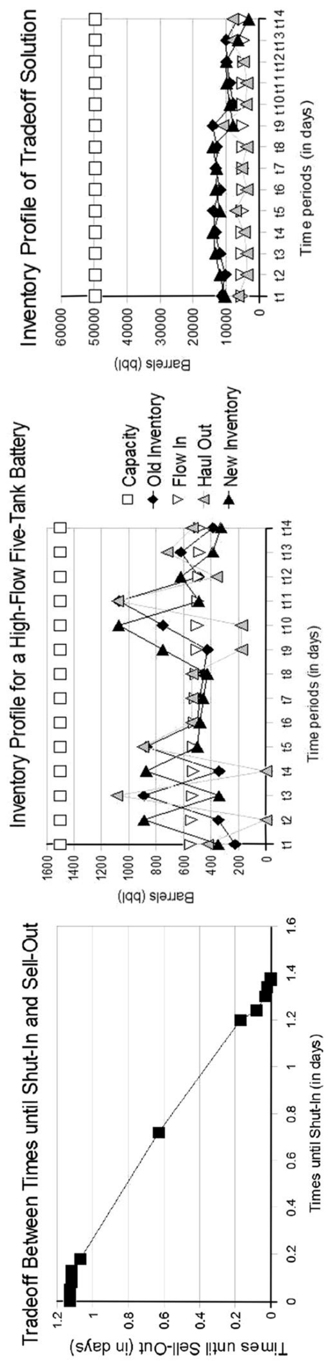

Fig. 5 Tradeoff solutions and inventory profiles for the corresponding tradeoff solution

Computing the corresponding Pareto curve for the bicriteria problem with TSI and TSO as objectives, that is plotted on the left of Fig. 5, we can see the above values at the lower right and upper left end points where maximum TSI and TSO are attained when the respective other objective is reduced to zero. Hence, the tradeoff between TSI and TSO becomes clearly visible and gives rise to a particular tradeoff solution in the approximate center of the Pareto curve, which was obtained using the combination of a min-max and weighting method. Interestingly, in agreement with our decision to use equal weights for TSI and TSO in our theoretical tradeoff analysis in Sect. 4, this point corresponds to the equal weighting of TSI and TSO with objective values of $4,102,774 for revenue, 77,940 bbl for total haul, and 0.72 and 0.63 days for TSI and TSO, respectively. The corresponding inventory profile for the same high-flow battery from Figs. 3 and 4 is depicted in Fig. 5 and shows how the resulting dispatch schedule keeps a sufficient yet safe inventory level around 600 bbl, which also approximately matches both the average flow and production over the full planning period. In particular, the generally smaller and better controlled inventory of this compromise solution is also apparent from the aggregated profile of the set of all 34 selected batteries, which verifies the potential success of our model to find efficient dispatch schedules that also achieve more desirable tradeoffs between our different decision criteria.

6 Conclusion

In order to meet the continuously growing demand for oil products and natural gas, many energy companies face increased logistical challenges while looking to expand or develop their production in previously unaccessible locations, such as the Wattenberg field in northeastern Colorado. Based on insight and real-life data from one of the most successful companies producing in this area, this paper specifically addresses the collection and subsequent shipment of the company's produced oil from a large set of geographically distributed storage location or batteries to several different purchasers and customer markets. Due to the lack of a pipeline infrastructure, the company currently uses a heterogeneous fleet of trucks that must be contracted from third-party hauling companies and allocated in a flexible manner so to maximize revenue and sales, and to avoid the risk of production shut-ins that occur when batteries reach their capacity before they are scheduled for service.

To support dispatchers with this task, we have created a multicriteria optimization model that represents the current oil load dispatch and hauling operations at Noble Energy for the computation of efficient, multi-period planning schedules and for systematic decision and tradeoff analysis. After a detailed description of all model decisions and our resulting formulation with the ability to incorporate split loads, which means that trucks can be sent for partial loads to multiple batteries, we have demonstrated how to use its solutions to visualize and analyze dispatch schedules and resulting inventory profiles, and to subsequently quantify selected tradeoffs between the different decision criteria. In particular, we have discussed the tradeoffs associated with split loads that revealed hidden opportunity costs among revenues, sales, and shut-ins, and we have highlighted the effect of minimum inventories to compromise shut-in avoidance with guaranteed deliverability. Having used a multicriteria approach to find dispatch schedules that can achieve such a compromise, this paper clearly highlights the advantages of multi-objective over single-objective solutions.

Possible extensions of our work and model that can be considered in the future include decisions on current parameters such as battery capacities and minimum reserve levels, the formulation of new or other objectives for shut-in avoidance and deliverability, and stochastic simulations to further analyze some of the inherent operational variability. While our current choices of parameters is informed by a statistical analysis and estimates from real but deterministic data, a similarly careful stochastic representation is likely to enable additional insights and possibly extend the feasible planning period from a few days to a longer time. This will not only create additional reliability and robustness of battery dispatch and service schedules, but also facilitate the contract negotiation of the company with its hauling partners and markets. Finally, we believe that the model in this paper is flexible enough to also be generalized to related operations in the energy industry and other sectors, and thus offers a host of opportunities for further research and interesting new applications.

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