Supply Plane Scheduling: Efficient Operation of Air Separation Units in Steel Plants

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Abstract

Production scheduling in industrial plants has been a long studied topic in Planning and Scheduling research and practice. This literature has primarily focused on scheduling the primary *production plane* to optimize the schedule of producing the main component e.g. the production of iron, paper production etc. This paradigm assumes that the energy and material required for the main production plane will always be available. So long as the primary production schedules obey the capacity constraints of the energy and material supply, the schedule is optimized. However, the increasing cost of energy and material has necessitated the study of their supply i.e. optimized scheduling of the *Supply Plane*. We study the challenges faced in this type of scheduling and how it is different from the scheduling of the primary production plane. As a case study of supply plane scheduling, we take the case of the air separation units in iron and steel industry. We describe the current practice, the possibilities for applying planning and scheduling, how to model the physical machines involved, and then describe an MILP based approach for scheduling. We provide experimental validation of the models, and discuss how they were used to generate schedules that optimized the costs of a real Iron and Steel Plant.

Introduction

All industrial plants can be thought of abstractly as taking a raw material and converting it to finished goods. This aspect, which we will refer to as the *production plane* has been the subject of intense study for a long time, and a lot of work has been done on planning and scheduling to control the operations of converting the raw materials into finished goods (Sinha et al. 1995; Dutta and Fourer 2001; Zheng et al. 2010). However, there is another plane, which we call as the *support plane* which is required for supporting the production plane. This consists of the energy and materials that are required for executing the operations of the production plane. The captive power plants, decisions to purchase power from the grids, the utilities, the water treatment plants, pumps for pumping this water, air separation units, gas storage units, coal gas plants, heat exchangers and many other equipment belong to this plane. High cost of energy and support materials is driving the need for planning and scheduling of the operations in this plane. Most of the work in planning and scheduling has been concerned with the reduction of energy costs, and specific process optimizations (Dutta and Fourer 2001; Zheng et al. 2010), and deal with specific problem dependent models. However, for achieving the goals of Enterprise Wide Optimization, it is essential to have models that are abstract to be applied across several different use cases, while at the same time have a strong connection to the underlying problems so as to be easily usable (see for example page 1848, in article (Grossmann 2005)). While some of the work on planning and scheduling of chemical reactions can be thought of as belonging to the support plane, it largely ignores the fact that the support plane is governed by the demands of the production plane. Sometimes, this results in schedules that are not in tune with the production plane plans.

In this paper we study one key component of the support plane of large iron and steel plants, the air separation units. The modelling and results presented here are based on our experience of investigating the efficiency of the air separation units as a support plane for a steel plant in India (due to confidentiality reasons, we cannot mention the name of the plant). These units are used for supplying oxygen, nitrogen and argon gases for the various operation in the steel plant. We describe (i) their operations and management requirements and (ii) their physical attributes, that together pose significant challenges to implement planning and scheduling solutions. We develop a scheduling solution based on MILP. More than the MILP, it is the interplay of management decisions and the modeling of the systems towards a practically usable solution that makes our work interesting. We then identify key characteristics of the problem that extend to the broader context of planning and scheduling for support plane.

We begin by describing the management of the plans and schedules of air separation units in Iron and Steel plants.

Support Plane Planning in Steel Production

A typical iron and steel plant consists of several furnaces (usually blast furnaces and electric arc furnaces) that are one of the main components of the production plane (other components being hot rolling and cold rolling mills). The main task of the support plane is to supply fuel and materials for

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the various processes occurring in these furnaces. The support plane consists of coking ovens, coal supply, and sources of oxygen, nitrogen and argon. The requirements of oxygen and nitrogen for typical iron and steel plant is very large. Due to this, most plants maintain in house air separation units that suck in air and split it into oxygen, nitrogen and argon (both gas as well as liquid form). The air separation technology is usually the cryogenic air separation process. The main source of energy for these plants is electricity, and the cost of this can be a large part of the energy cost of iron and steel plants. This necessitates the search for ways of reducing the energy usage.

The factors that govern the schedule of the production plane are the confirmed customer orders and forecasted demand. In turn, this schedule dictates the schedule of the support plane. Since the customer orders are the primary drivers of the production plane, the schedule of the support plane is expected to be such that it does not hold up the schedule of the production plane. Any maintenance in the support plane is typically planned well in advance, and steps are taken to compensate the production plane for any production loss. A high redundancy is also present to compensate for any kind of unplanned emergency shut-down of any equipment in the support plane.

A typical production schedule of the air separation units is done as follows. A central planning committee decides the monthly/weekly production plan for the production plane. This is then drilled down to a daily schedule for the production plane. The daily requirement of oxygen, nitrogen and argon is calculated, and this is given to the Air Separation Unit Management. The production plane plan may then be further drilled down to a finer time granularity, but this information is typically not passed on to the air separation unit management. Traditionally, key metric that is used to measure the performance of the air separation unit management is the monthly *venting* of gases that have been produced i.e. the amount of oxygen, nitrogen and argon that is separated, but not used. However, this is subject to the requirement that the production plane requirements are completely met. Any violation of this leads to strong negative reviews of the air separation unit management. Since the action faced for high venting is mild compared to that for violating the production plane requirements, the air separation units are typically run at full capacity. The only optimization that is undertaken is that they may shut down some of the air separation units, or run some at lower capacity, when one or more of the furnaces is taken down for maintenance that lasts for at least a day.

However, the trend now has been to measure the performance of the air separation units based on their total operating cost, most of which comes from the electric power consumed. Due to this, more information of the production plan schedules is shared with the support plane. This creates the opportunity for applying scheduling techniques to minimize the energy consumption, minimize the venting and still meet the production plane demands. However, this requires knowledge of the details of the physical characteristics and operation of air separation units.

Air Separation as a Support Plane

The air separation systems consist of air separation units, connecting pipes, gas tanks for storing gaseous oxygen, nitrogen and argon, liquid tanks for storing liquid oxygen, nitrogen and argon, and evaporators for evaporating the liquefied gases to gaseous form. The gas tanks are usually connected as buffers to the demand points, so there is no active filling or emptying of the gas tanks; the demand point consumption determine the amount present in the tanks. Thus these tanks only help in dealing with sudden fluctuations, and do not play any role in the schedule. The liquid tanks usually consist of vacuum tanks, which are essentially two tanks, one inside the other, with vacuum in between, so that the liquefied gases get very little external heat due to conduction. Thus, they consume very little power. The evaporators usually are pipes that carry the liquid. They are simple pipes that heat the liquid by conduction of heat from the air to the liquids in the pipe. Thus they use external heat and do not consume any real power (at most a few industrial fans that drive the cool air away from the evaporator, so that the surrounding air can pass by it). The liquid tanks are usually used for storage of emergency supply (buffer) and also for meeting any sudden fluctuations. There is a minimum amount of liquid that has to be present at all times in the tanks, so that they can be used when faced with an unplanned shut down of the air separation units. Thus the main use of the liquid tanks in scheduling is to provide buffer capacity. Their power consumption is negligible. The main source of power consumption are the air separation units.

Air Separation Units

Cryogenic air separation units (ASU in short) suck in air from outside and cool it to low temperatures at which the gases liquefy and separate out. The gases produced are gaseous oxygen (GOX), gaseous nitrogen (GAN), and gaseous argon (GAR), while the liquids produced are liquid oxygen(LOX), liquid nitrogen (LIN) and liquid argon (LAR). These machines are usually very large structures (several storeys high), and have continuous operating points. However, not all operating points are usable as they may produce impure gases. Typically the recommended operating points are fixed for example 100%, 90%, 60%, 30% and off. However, one cannot switch rapidly from one point to the other, nor can one switch from one state to any other state. For example, if it has to be taken from off state to 30% stage, then the air separation unit has to be first taken to the 100% state (even though the ASU passes through the 30% state on the way, the gas quality will be low due to impurities); it has to be taken from the 100% pure gas production state to the 30% pure gas production state. This can be described by a state transition diagram as shown in Figure 1.

The task of taking the ASU from one state to another requires some experience in handling the machines and complex control systems, and any state transition is a slow process, at times requiring manual intervention and can last up to several hours. During a state transition, the gases produced from the ASU are impure, and are typically let out into the atmosphere. These do not count towards venting, as these are not pure gases. For the same reason, the liquids produced by the ASU during state transitions are not usable, and are typically taken in tanker trucks and evaporated into the atmosphere (these costs of tankers and trucks are usually very small, and amortized across many operations).

Each of the fixed pure operating points have their own production rates for the various components (liquid and gaseous forms of oxygen, nitrogen and argon). Thus to optimize the schedules, against a given daily demand from the production plane, we can control the operating points of the ASU's to minimize venting and energy usage. However, the main issues for this type of scheduling are the following.

1. The transition times from one operating point to another are not fixed. They can vary from a known minimum to a known maximum. Further, no typical values for these times, their distributions are known, and it may not be possible to model them, either due to the lack of experimental data or due to the many factors that govern these times.
2. The air separation management will not accept any schedule that involves a large number of transitions between different states. However, they may not be in a position to specify a maximum rate of switching, and prefer to see several different solutions, of which they can choose one. In particular, the instruction that the ASU be taken from one state to another is usually not automated (the control system is automated, but the command for the transition needs human intervention). Thus, it is essential that the ASU schedule has small number of transitions.

In addition to the above, we have to ensure that at all times, the achievable supply is at least equal to the demand from the production plane. In the next section we formally describe the scheduling problem we are dealing with and present an MILP formulation for solving it.

System Modeling and Problem Formulation

Given time-varying demand for each of the gases, the configuration of the ASUs, the capacity of the liquid tanks, find a schedule that minimizes the energy consumed, the total venting, and minimizes the amount of switching between different states by the ASUs. We begin by first modeling each of the entities in the system.

Modeling Demand

As mentioned earlier, we are scheduling in the support plane. The production plan is assumed to be fixed in advance. The job of the support plane is to provide the required amount of each type of gas, or say that the production plan is infeasible. However, infeasibility is usually rare, since industrial plants are over provisioned and sized, and the rules or optimized methods that fix the production plans are designed to ensure feasibility. The demand for each type of material is then obtained by a predetermined formula consisting of a simple multiplier or by forecasting the demand based on past experiences. Usually, depending on the grades of the product in the production schedules, and the variation in quality of the raw materials, the demand can vary slightly. Thus excess provisioning is built into the demand calculation. We assume that the demand for each gas at each time is completely specified. The actual process (e.g. the electric arc furnace reaction) may require the gas at a very specific pressure and temperature. However, this operation is carried out in a different equipment and does not fall in the purview of ASU. For our purposes, we can assume that the gases are supplied at fixed pressures. This is done by using the combination of the gas tanks and adjusting the production rates slightly. The granularity of each slot can vary for 30mins to a few hours, depending on the data. We index scheduling horizon in terms of timeslots by $T = \{1, 2, \ldots, H\}$, and the gases by $g \in \{GOX, GAN, GAR\}$; we refer to the demand for type g at time t by $D_t(g)$. Note that there is demand only for the gases. The liquids are only used after evaporation to the corresponding gaseous form.

Modeling ASUs

The number of ASUs is usually from two to eight for typical steel plants, and is a combination of medium sized and large sized ASUs. We number the ASUs by a number from 1 to n, and refer to the i^{th} ASU by i, $i \in [n] = \{1, \ldots, n\}$. The ASUs are typically calibrated to operate in a fixed range of production rate. This is usually done when sizing the plant, so that operational decisions on the capacity of the plan can be guaranteed (the website (Universal-Industrial-Gases) discusses more on this). Thus an ASU is calibrated to operate within a certain production range, and the change of rate is controlled by changing the air suction into the ASU. Note that for some type of ASUs, the rate of production will also depend on the ambient temperature of the air, and the purity of the air. However, these variations are minor and can be neglected for our purpose. Thus we may assume that the rates of production can be fixed, given the operating points.

Modeling Operating Points We now present the operation of an ASU in terms of its different operating points and the transitions between those operating points.

1. *Operating Points:* The fixed set of operating points of an ASU, say the ith, is denoted by $OPER_i$. Each operating point is characterized by the production rates of the different gases and liquids, and the corresponding power consumption. A typical unit will have about 2 to 5 operating points, including "OFF". We will denote the operating points of ASU i by $OPER_i = \{O_{i0}, O_{i1}, \ldots, O_{i\ os_i}\}$ where os_i is the total number of distinct operating points of i. We assume that for all i, O_{i0} corresponds to the "OFF" state of the ith ASU.
2. $R_{ij}(p)$ The production rate of any type of gas *GOX, GAN, GAR* or liquid *LOX, LIN, LAR* by i at operating point j is given by $R_{ij}(p)$, where p denotes the gas or liquid.
3. *Transitions:* Each ASU can make direct transitions only between certain states. Thus each transition corresponds to an ordered pair of operating points. A transition from state O_{ij} to state O_{ik} is denoted by T_i^{jk}. Each T_i^{jk} is characterized by two parameters.
   (a) *Min Transition Time :* Denoted by $m(T_i^{jk})$, this repre-

sents the minimum time required for making the transition from state O_{ij} to state O_{ik}.

(b) *Max Transition Time :* Denoted by $M(T_i^{jk})$, this represents the maximum time required for making the transition from state O_{ij} to state O_{ik}.

It should be noted that the model of the ASUs assumes memoryless transition times i.e., the time taken to transition from one state to another is independent of the history of how the ASU got to that state. This is strictly an idealized assumption, made possible by rolling any hysteresis information into the min and max transition times. Based on our experience, we make a simplifying assumption that there is one way of transitioning from one state to another (although in reality, there would be alternatives with minor variations). Whenever an ASU makes a transition from state O_{ij} to O_{ik}, the time taken for this transition is at least $m(T_i^{jk})$ and at most $M(T_i^{jk})$. The actual realized value of this time is not known in advance. Since there are large number of features of the operations that may determine this time and since, not all of them are instrumented, the current state of affairs do not allow us to derive this number via a statistical model. Therefore, we use the paradigm of *Robust Optimization* (Bertsimas, Brown, and Caramanis 2011), and the concept of *Transient States*.

We capture the different operating points of an ASU and the transitions between them as a state transition diagram as shown in Figure 1. In this figure, the state transition diagram of an ASU that operates in states *OFF, 50%, 100%* is shown. Each edge marked with the numbers corresponding to the minimum and maximum transition times (in hours) for that transition (unmarked edges indicate instantaneous transition).

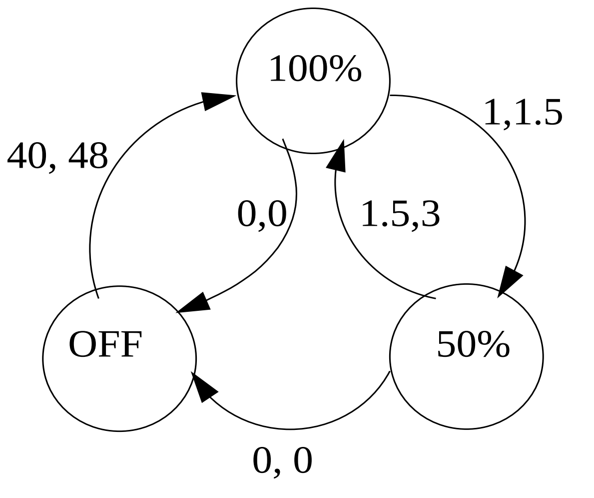

Figure 1: State Transition Diagram

All the states shown correspond to valid states in which the air separation can operate indefinitely. While some of the intermediate states it enters during transition cannot last long. For the purpose of using the state transition diagram into constraints in our MILP model, it helps to associate the minimum and maximum time that an ASU can spend in a state as properties of the state. So, we modify the representation to that in Figure 2 where the transition edges can be treated as immediate. This requires additional transient states to represent time taken by transitions. For example, the transitions corresponding changes from *100% to 50%* and from *50% to 100%* are shown as T2 and T1 in the figure 2. We shall denote the transient states introduced as $TRAN_i$.

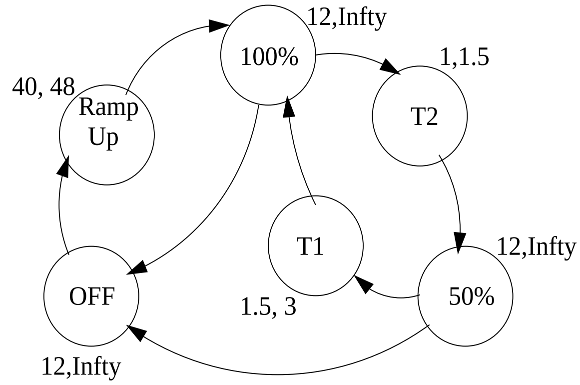

Figure 2: States with Persistence

Each state in this representation has two durations associated with it: *Minimum Persistence* and *Maximum Persistence*. They are defined as the minimum and maximum duration that a node can spend in that state. For states corresponding to *valid* states, i.e., states corresponding to operating points, the maximum persistence will be set to infinity, while the minimum persistence is set to a suitably large value to prevent rapid switching. In our model we set this time to be 12 hours, insisting that once the ASU makes a transition to a particular operating point, it remains at that point for at least 12 hours. For the nodes corresponding to transient states, the minimum and maximum persistence are set to be the minimum and maximum end of the time range required for the actual state transitions that the transient node is facilitating. Note that the transition from any operating point to the OFF state is instantaneous. Physically this corresponds to switching off the air supply, and reducing the power. This operation usually takes a few minutes, so in the scheduling problem, it may be assumed to take place instantaneously. When the ASU is in transition, the purity of the products is not guaranteed. So, we will treat the production rate of the ASU during transient states to be zero.

In the operation of the ASU, the transition from the OFF state is always to the 100% state, with no intermediate 50% state. This is to ensure the purity of the gases obtained. The cycle from OFF to 100% is called as the *Ramp Up cycle*, and has several parts, since each of the products have different ramp up times. The ASUs in the particular case of steel plant we worked with had the following ramp up characteristics. When the ASU is switched on from an OFF state, the initial 33 to 36 hours, the products produced if any, are too impure to be used. After that, the production of high purity usable GOX and GAN starts. After about 4 to 6 hours after

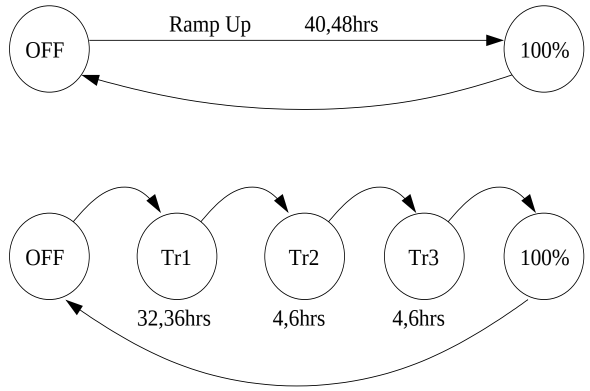

Figure 3: Ramp Up Cycle

this, the production of LOX starts. Finally, after another 4 to 6 hours, the ASU enters the 100% operating point and all its produces are produced. Thus, the transition from OFF to 100% state is modeled using 3 intermediate transient states *Tr1, Tr2, Tr3*, and is indicated in figure 3, where the lower figure has the maximum and minimum persistence of the intermediate states indicated.

We use the following notation.

- $O_i = OPER_i \cup TRAN_i$. The j^{th} state in O_i shall be denoted by O_{ij} (irrespective of whether it is in $TRAN_i$ or $OPER_i$)
- $M(O_{ij})$ refers to the Maximum Persistence in the state O_{ij}
- $m(O_{ij})$ refers to the Minimum Persistence in the state O_{ij}

For a transient state O_{ij} corresponding to a transition from valid operating points O_{is_1} to O_{is_2}, we have

$$m(O_{ij}) = m(T_i^{s_1 s_2}) \tag{1}$$
$$M(O_{ij}) = M(T_i^{s_1 s_2}) \tag{2}$$

We let $\mathcal{N}^-(O_{ij})$ to denote the set of all states from which the ASU can transition to the state O_{ij} (this includes both valid and transient states).

Modeling Constraints The main operational decision that needs to be taken with respect to each ASU is essentially the amount of time it spends in each of its state and the sequence of the transitions. For the valid state, i.e, the states that correspond to operating points, the ASU management is in control of the time spent in the state. Whereas, the time spent in the transient system is uncertain and difficult to control. In the transient states, the system may spend any amount time in the range of minimum and maximum persistence. We want to produce *robust schedules* that remain feasible irrespective of the actual amount of time spent by the system in the transient states during its operations. For this purpose, we use the *Robust Optimization* framework.

The main idea in the robust optimization is to find solutions that work even under worst setting of the parameters that are uncertain. In our setting, the parameters that are uncertain are the transition times. However, we know the maximum and minimum possible values of these transition times. This corresponds to the case of *bounded uncertainty*. So we can achieve robust solutions by setting the minimum persistence to be equal to the maximum transition time. This ensures that the transition times used by the MILP model are in fact the maximum possible. This MILP is feasible as is given by (Lin, Janak, and Floudas 2004) When the schedule is implemented, the decisions to be taken correspond to the times when the ASU is to be switched from one state to another. For any given realization of the transition times when implementing this schedule up to a time t, the rest of the schedule continues to be feasible.

To capture the constraints corresponding to the operation of the ASUs in the MILP model for scheduling, we use the following decision variables.

- x_{ijt} - boolean decision variable which takes the value of 1 if ASU i is in state $j \in O_i$ at time slot $t \in T$; else it is 0
- y_{ijt} - boolean decision variable which takes the value of 1 is ASU i enters state j at the start of time slot t; else it is 0.

Since an ASU can be in only one state at a time, the following set of constraints should be true.

$$\textstyle\sum_{j \in O_i} x_{ijt} = 1 \quad \forall i \in [n], t \in T \tag{3}$$

ASU state transition constraint: An ASU can transition to state O_{ij} only from it's allowed predecessor states. Therefore, the following constraints should hold.

$$\sum_{k \in \mathcal{N}^-(O_{ij})} x_{ik(t-1)} \geq y_{ijt} \tag{4}$$

This ensure that if at any time, the ASU transitions to state O_{ij}, then it must have been in some state in $\mathcal{N}^-(O_{ij})$. We also capture the state transitions as follows.

$$y_{ijt} \leq x_{ijt} \tag{5}$$
$$y_{ijt} \leq 1 - x_{ij(t-1)} \tag{6}$$
$$y_{ijt} \geq x_{ijt} - x_{ij(t-1)} \tag{7}$$

Constraint for maximum persistence: The maximum time that an ASU i can remain in state O_{ij} once it enters it is $M(O_{ij})$. This means that some time slot t in any block of $M(O_{ij}) + 1$ contiguous slots, x_{ijt} should be zero. Let $\Gamma(t)$ be the contiguous set of $M(O_{ij}) + 1$ time slots ending with slot t. Then, the constraint for ith ASU at time slot t for the state O_{ij} translates to:

$$\sum_{\tau \in \Gamma(t)} x_{ij\tau} \leq M(O_{ij}) \tag{8}$$

Note that for the initial $M(O_{ij})$ time slots, $\Gamma()$ extends before the first slot of the schedule. For those cases, we use the initial conditions of the ASU at the start of the schedule, to obtain an equivalent constraint inequality.

Constraint for minimum persistence: This constraint ensures that the ASU_i stays in a state O_{ij} for at least $m(O_{ij})$ time slots. For any time slot t, we let $\mathcal{T}(t)$ denote the contiguous set of $m(O_{ij})$ time slots starting with t. Then, if the ASU enters state O_{ij} at time t, the following constraint ensures that it remains in that state throughout $\mathcal{T}$. Then, the constraint for ith ASU at time slot t for the state O_{ij} translates to:

$$\sum_{\tau \in \mathcal{T}(t)} x_{ij\tau} \geq m(O_{ij}) y_{ijt} \tag{9}$$

Note that for the initial few intervals, we take into account the initial state of the ASU and the same logic to obtain equivalent constraints. However, unlike the maximum persistence case, we also need to separately take into account the last few slots till the horizon. Thus if the ASU makes a transition to a state O_{ij} at time t which is no more than $m(O_{ij})$ time slots from the horizon H, we simply deduct the excess time slots beyond H in $\mathcal{T}(t)$ from $m(O_{ij})$ on the right hand side of the above inequality.

Liquid Tanks and Gas Tanks

Modeling Operations The gas tanks are usually containers that act as buffers between the demand points and the supply pipes coming from the ASUs. Depending on the difference of pressure of the supply and the demand, the gas tanks are automatically filled in or emptied. There is no active intervention for deciding when to supply from the gas tanks. Therefore, gas tanks do not need to be modelled as such. We models the liquid tanks as follows.

While the solution that we developed for the steel plant takes into account the network of connections from ASUs to particular tanks, for the purpose of the paper, we will assume that every liquid tank can be filled from every ASU. This allows us to simplify our presentation by aggregating the tanks of each type of material into one large tank. Thus we will assume that there are three tanks, one for each type of liquid $\ell \in \{LOX, LIN, LAR\}$. Corresponding to each liquid tank, there are three parameters in the model.

- cap_ℓ indicates the total storage capacity for the liquid ℓ
- $init_\ell$ indicates the initial amount of liquid ℓ that was stored
- SS_ℓ indicates the safety stock of ℓ that is to be present in the system at all times.

The amount of safety stock is decided by the ASU management and is used in case of any unforeseen incidents like the failure of any ASU.

Modeling Constraints The operational constraints that the liquid tanks have to meet can be specified in terms of three quantities: the total amount buffered in the tank, the amount of liquid coming into the tank at every time step, and the amount of liquid going out of the tank at every time step. While there are operational constraints are specified in terms of these quantities, these quantities themselves need to be determined by the optimization engine, i.e, they are decision variables.

For every liquid $\ell \in \{LOX, LIN, LAR\}$ and for every time $t \in T$, we let

- $z_t(\ell)$ - the total buffered amount of liquid ℓ
- $z_t^i(\ell)$ - the total amount of liquid ℓ flowing into the liquid tanks from the ASUs
- $z_t^o(\ell)$ - the total amount of liquid ℓ evaporated from the liquid tanks. Note that in the text, at times we will $z_t^o(g)$ for $g \in \{GOX, GAN, GAR\}$, in which case this is to be interpreted to mean $z_t^o(LOX)$, $z_t^o(LIN)$ and $z_t^o(LAR)$ respectively, and refers to the amount of gas produced by evaporating a corresponding amount of liquid. In our model, all products were measured in *tons*. Hence the evaporation of one ton of liquid gives one ton of gas (assuming zero loss).

The following operational constraints have to be satisfied at every time $t \in T$ and every liquid $\ell \in \{LOX, LIN, LAR\}$.

Liquid tanks capacity constrains: The total amount of liquid present in its tank should not exceed the capacity of the tank.

$$z_t(\ell) \leq cap(\ell) \tag{10}$$

Mass conservation at liquid tank: In reality, there could be a loss of negligible amount of liquid stored in the form of letting out of its gaseous form that occurs due to evaporation. However, we ignore this loss. So, the change in amount of liquid that is present at the end of a time slot in any tank is just the difference between what is filled in and what is taken out of the tank.

$$z_t(\ell) - z_{t-1}(\ell) = z_t^i(\ell) - z_t^o(\ell) \tag{11}$$

Minimum liquid stock constraint: In case of any malfunction of the ASUs, it is essential to have a *safety stock* of liquid that can be evaporated to supply the demand. This safety stock is specified by the ASU management, and we ensure that this amount of liquid is always present throughout the schedule.

$$z_t(\ell) \geq SS_\ell \tag{12}$$

Further, the total amount of liquid that is filled into the liquid tanks at any point of time is no more than what is produced. The liquid that is produced in excess (i.e. cannot be stored in the liquid tanks due to capacity constraints), is usually either evaporated as waste, or filled in tanks and sold to buyers like welding shops and hospitals. So, we allow excess production of liquids (the inequality below), but do not take into account the potential revenue of selling the excess to other buyers.

$$\sum_{i \in [n], j \in O_i} x_{ijt} R_{ij}(\ell) \quad \geq \quad z_t^i(\ell) \tag{13}$$

Goals For Scheduling

The objective of the scheduling is to minimize the total cost. The cost is largely from the electricity consumed. However, getting the actual amount of electricity consumed is very difficult. This is because the records maintained by the captive power plant is aggregated at the plant level (and is not split into consumption of different units). So, we decided to use the total production of the different gases and liquids as a proxy for the cost function. In particular, since the total production of gaseous oxygen GOX is the primary concern for the ASU management, we minimize the total GOX produced, subject to the constraint that the demand for al products is met at all times. Thus, our optimization function is as follows.

$$\min \sum_{i\in[n],j\in O_i,t\in T} x_{ijt}R_{ij}(GOX) \qquad (14)$$

The main constraint that the schedule should obey is that the demand for all the gases and liquids be met. The liquids are not used directly in the furnaces. They are evaporated to produce the gaseous forms that are fed into the furnace. Therefore, the demand satisfaction constraint is modelled as follows.

$$\forall t \in T, g \in \{GOX, GAN, GAR\}$$
$$z^o_t(g) + \sum_{i\in[n],j\in O_i} x_{ijt}R_{ij}(g) \quad \geq \quad D_t(g) \quad (15)$$

The state transitions for each of the ASUs are specified in terms of hours. However, the ASU management received their demand from the production plane at the level of a day. So, we divided the demand of the production plane for a day into the same granularity in terms of hours as that used in the transition times. So, our demand profile within a day is uniform.

Apart from the cost, expressed in terms of the total GOX produced, another important metric from an operations perspective is the number of state transitions of the ASUs as per the schedule. It is essential to keep the number of transitions low because each transition adds to the complexity of the operation and increases uncertainty of the desired outcomes. One of the ways to generate a schedule with small number of state transitions is to construct sparse solutions. We adopted a simple mechanism to ensure sparse solutions. We allowed the ASU managers to control two parameters that go into the optimization model: an appropriate window of time over which the number of transitions is to be controlled and the minimum duration of operation in each of the valid operating point of an ASU. Specifically,

- W is a user specified duration used for evaluating frequency of transitions.
- NT is user specified maximum number of transitions allowed in any time window of W slots
- w_{it} is an integer decision variable that counts the total number of transitions by the ASU i in an interval of W slots, ending at t.

We count the number of transitions of each ASU to states corresponding to operating points i.e., states in $OPER_i$, in each window of size W using the y_{ijt} variables (recall that y_{ijt} specifies if the ith ASU entered state j at time t), and bound that by NT. This constrains the number of transitions that the ASUs make. Let $\mathcal{W}(t)$ denote the interval consisting of W slots, ending at t.

ASU Type	Operating Points	Gas Rate GOX/GAN (Nm3/hr)	Liq Rate LOX/LIN/LAR (tons/day)
T_1	100/50/OFF	11083/4000	10/0/10
T_2	100/50/OFF	10733/8000	0/5/10
T_3	100/90/50/OFF	11083/4000	10/0/10
T_4	100/90/50/OFF	22166/8000	20/0/20

Table 1: ASU Configurations

$$\forall t \in T, i \in [n] \qquad (16)$$
$$w_{it} \leq NT \qquad (17)$$
$$w_{it} = \sum_{O_{ij}\in OPER_i \text{ and } t'\in\mathcal{W}(t)} y_{ijt'} \qquad (18)$$

Besides the above constraints, we also put in initial conditions corresponding to the initial amount in the tanks, the initial states and duration in that state for the ASUs.

The final MILP consists of the objective in expression (14), and the constraints from (3) to (16), along with initial conditions and boundary conditions.

Experimental Set-up and Results

The MILP model described was the basis for an advanced scheduling solution we developed for demonstrating the benefit of optimized scheduling for the steel plant we worked with. The model described in this paper was implemented in ILOG ODME and solved using the CPLEX solver. Since the data from the clients is confidential, we used the characteristics of their data to construct test data for experimentally validating the model. We describe this data and the experiments below.

System Configurations Used

The typical mid sized iron and steel plant has about four to five air separation units. We constructed 4 types of ASUs, denoted by T_1, T_2, T_3, T_4. Of these, T_1, T_2, T_3 are mid-sized units, while T_4 is a large unit of twice the production capacity of T_1. The operating points and production rates for each of them is tabulated in table 1. The rates mentioned are for the case of 100% operation. The rates for the 90% and 50% states were obtained by scaling by 0.9 and 0.5 respectively. In real life, the rates for the 50 percent operation are not strictly half that of the 100 percent operating point. These have to be obtained from the observations conducted by the Air Separation Plant Management. However, for the sake of empirical validation, we assume that the rates are scaled depending on the percentage of the operating points. The numbers used in the experiments are similar, but not identical to the numbers of real air separation units that are used by the iron and steel plant we worked with. It is also representative of the scenarios in most other plants with in-house ASUs. The rates for the gas production are specified in terms of **Nm3/hour**, and of the liquids in terms of **tons/day**, as is the convention for such equipment. The ramp up cycle for each

System	Config
S_1	T_1, T_1, T_3
S_2	T_1, T_2, T_3, T_4
S_3	T_1, T_1, T_3, T_4
S_4	T_1, T_1, T_4, T_4

Table 2: System Configurations

air separation unit uses the data shown in figure 3. We constructed 4 different configurations with these air separation units as shown in the table 2.

Demands Used

The time horizon used for scheduling was 31 days. We constructed demands with 4 hours granularity for the full 31 days. Since the plants are designed to handle the the demands that typically arise, we construct the demand by taking into account the maximum demand that the plant can satisfy, with a random variation from 80% to 100% of the maximum capacity for each of the gases *GOX, GAN, GAR*. Further, we introduced *maintenance periods*, where the demand reduced to about 40-60% of the maximum possible for a duration of 2 days at a stretch, followed by a day of 75% demand. We experimented with demands with one, two and three randomly placed maintenance periods in the scheduling horizon.

Transitions Allowed

As already mentioned, we ensure that the air separation units stay for at least 12 hours in any operating point they enter. Besides this, we varied the window size (W) from 0, 1, 3, 5 and 7 days, with at most one change of operating point allowed in each window (i.e. an NT of 1).

Empirical Evaluation

For each of the 4 system configurations, we experimented with different combinations of demands and allowed transitions. Due to space consideration, we show the results for only S_1 and S_2. Results for S_3 and S_4 which are omitted also show similar benefits. The column "W/NT" gives the window and number of allowed transitions in the window and the column "Transitions" refers to the total number of transitions in the optimized schedule. The rows with $W/NT = 0/0$ refer to the case of 100% rate and no transitions. As is to be expected – the gas produced increases as the window size W is increased while keeping NT the same. To measure the savings achieved, we used the amount of gas produced in the $W/NT = 0/0$ setting.

Following are our main observations: (i) Since we do not associate any cost with transitions, we can meet the demand with less production as the number of allowed transitions increased (the 1/1 setting for W/NT achieves lowest production in all cases), (ii) When the window is set to 7 days, the optimizer is not able to take any advantage and produces the same amount of gas as the $0/0$ setting, (iii) The point of least gain is $5/1$ setting which achieves a saving of *GOX* production is roughly 12% for S_1 and 14% for S_2; the saving of *GAN* production is roughly 10% for S_1 and 13% for S_2.

These results point to the potential savings opportunities by focusing on support plane planning and scheduling. Note that the production value are not monotonic with the number of transitions when compared across two demands with different maintenance periods. This is because the maintenance breaks occur at different points of time, so a feasible schedule for one demand may not be feasible for another demand.

System $S_1 =< T_1, T_1, T_3 >$			
W/NT	Transitions	GOX(tons)	GAN(tons)
0/0	0	33744.29	12764.80
Demand with 1 Maint Period			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	26	29026.60	11144.90
3/1	8	29036.45	11165.13
5/1	8	29233.63	11227.60
7/1	0	33744.29	12764.80
Demand with 2 Maint. Periods			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	22	28537.41	10926.81
3/1	6	29273.30	11253.19
5/1	6	29873.47	11440.68
7/1	0	33744.29	12764.80
Demand with 3 Maint. Periods			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	28	26800.06	10338.65
3/1	12	27852.56	10734.93
5/1	6	29880.46	11440.75
7/1	0	33744.29	12764.80

System $S_2 =< T_1, T_2, T_3, T_4 >$			
W/NT	Transitions	GOX(tons)	GAN(tons)
0/0	0	56763.21	22848.68
Demand with 1 Maint Period			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	28	46261.50	18683.67
3/1	16	46853.34	19067.28
5/1	12	48833.92	19750.01
7/1	0	56763.21	22848.68
Demand with 2 Maint. Periods			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	36	46768.52	18855.10
3/1	18	48578.09	19699.58
5/1	12	49103.20	19995.08
7/1	0	56763.21	22848.68
Demand with 3 Maint. Periods			
W/NT	Transitions	GOX(tons)	GAN(tons)
1/1	24	46706.63	18809.58
3/1	20	47269.22	19198.07
5/1	18	48344.11	19739.14
7/1	0	56763.21	22848.68

Client Experience: In our interactions with the steel plant, we received data for one month. The plant was producing at full capacity, except for a period of 2 days when one of the furnaces was under maintenance. While running all the air separation units at 100% capacity was a good solution, our model was able to identify solutions that achieved a saving of 7% and the optimization model solved the instance in less than 10 minutes.

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