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Applying multidisciplinary logistic techniques to improve operations productivity at a mine

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Abstract This case study uses a surface mine to investigate multidisciplinary logistics analysis methods for improving refinery operations. Existing resource scheduling, inventory forecasting, and economic production quantity procedures have not been able to identify how to improve productivity. The objective was to locate and demonstrate proven techniques from operations research (and other related disciplines) which could be applied to solve logistics problems. Historical operations data along with a new sample ($n = 140$) were utilized for the analysis. Preliminary parametric tests failed, but later a multiple server queue model was developed by integrating non-parametric techniques, waiting line theory, stochastic probabilities, and break-even scenario analysis. Quantitative and qualitative data were analyzed, resulting in a solution to increase truck arrival rates by 10% which was projected to increase refinery utilization by 7–77%, thereby generating a potential productivity savings of $161,223.31 per year.

Keywords Decision making · Logistics · Surface mining · Multidisciplinary mixed methods · Case study · Statistical distributions · Waiting line theory · Queues

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1 Introduction

A mining company discovered the logistics planning methods being used applied hidden assumptions which may have indirectly led to decreased productivity and accidents at a refinery. The company was using two operations research techniques (forecasting and inventory economic production quantity), along with enterprise resource planning software (inventory, scheduling, general ledger, payables, and receivables). It wasn't necessarily that the software or underlying models were incorrect, but rather they no longer matched operational needs. This could happen to any company because logistics is impacted by terrorism, civil unrest, global warming, natural disasters, new technology, and better Internet connectivity. The interesting dimension in the spirit that "challenges taken for granted knowledge" [1], was not the solution per se but instead how the problem was resolved by integrating techniques from outside the logistics discipline.

The objective of the case study was to find sources of proven techniques which could verify "hidden assumptions" as well as better match the operational goals and production data. The research purpose was to illustrate how to select and apply proven techniques from other disciplines to solve logistics-related problems. Nonparametric statistical hypothesis testing was integrated with waiting line theory, stochastic probabilities, and break-even scenario analysis. Another research goal was to demonstrate applying mixed methods and case studies to logistics problems, as a way to stimulate practitioners to "think outside the box".

2 Literature review

Words can be deceiving (in any language) in that terminology differs, and in some cases, great solutions to problems may exist but they are overlooked since either the correct key phrase was not used in a search or in the index of a manual. More so, mathematical and statistical models can be confusing because “optimization is studied in many disciplines—each with its own terminology” [2].

It is a custom in many industries to purchase commercial software for automating operations [3, 4]. This is because “enterprise systems” are designed on mature best practices so companies can leverage proven automated techniques without having to either invest resources to develop and maintain proprietary software or do lengthy calculations manually [5, 6]. Logistics software for mining typically focuses on simulating the space and time relationships between mining equipment mainly in connection with transport systems [7], thus leaving shift scheduling to the human resources function, rather than optimize it.

Not surprisingly, logistics software may seem attractive to mining managers, so this term should be defined before we make any assumptions. A good logistics definition is quoted below to define this scope.

> Logistics is an application-oriented scientific discipline. It models and analyzes economic systems as networks and flows of objects through time and space (specifically goods, information, moneys, and people) which create value for people. It aims to supply recommendations for action on the design and implementation of such networks through accepted scientific methods. Scientific questions of the discipline are related primarily to the configuration and organization of these networks, and to the mobilization and control of flows. Its ultimate goal is progress in the balanced achievement of economic, ecological, and social objectives [8].

2.1 Where to find logistics techniques

From the above definition, it is clear that logistics is an applied science rather than a pure theoretical domain (it is not one where new models and theories would regularly be invented). Although the logistics definition fundamentally emphasizes planning as well as managing networks and flows of an organization’s value chain resources through time and space, the application of “how” that is done is left to “accepted scientific methods”. It makes sense then that logistics practitioners (such as this case study company) ought to make full use of theories and techniques from the related disciplines (especially operations research and applied mathematics), as well as leveraging commercial software (if applicable). However, when using techniques or software the assumptions must be noted, because there could be a miss-match between goals, data and proposed solutions.

There are numerous scientific methods defined across the disciplines which can be used in logistics. For instance, GoogleScholar estimated 651,231 results with the words “logistics” using an advanced search of “journal” publications. A search of “logistics” from a sample of peer reviewed economics and operations research journals in the ScienceDirect catalog returned 9,941 articles. There are 152 relevant topics explained in an operations research-management science handbook [9]. Exemplar methods include: Age Replacement, Ant Colony, Branch and Bound, Clustering, Consensus Building, Fuzzy Search, Genetic Algorithms, JIT, Linear Programming, Markov, MRP, Risk Analysis, Scenario Analysis, Percolation Theory, Simplex, Spanning Tree, Stakeholder Participation, Queuing, Wardrop Equilibria, Warrant Models, and many other techniques [9]. These techniques range from statistics and math (for quantitative data) to Analytical Hierarchy Process and consensus building (for qualitative data such as opinions).

Different logistics techniques can result in opposite decisions even when applied to the same situation. In fact, authors in *Logistics Research* may present novel techniques to solve similar problems (with different solutions). For example, if qualitative portfolio selection techniques such as brainstorming or hierarchical decision-making were applied to a logistics supply–demand problem, the results would probably be very different than a deterministic mathematical programming routine to minimize costs or maximize profits subject to constraints. Qualitative data techniques are often subjective processes that may depend more on intuitive knowledge and personality/mood of the decision makers rather than parameters. “Rules of thumb and intuitive reasoning may easily lead to poor decisions” [10]. More so, qualitative decision-making approaches can result in tied-choices (no clear single best solution). Nonetheless unusual qualitative data analysis techniques are published, such as assessing employee competencies to develop a transformation function and logistics model that can help in task scheduling problems [11].

In the quantitative category of techniques, linear/mathematical programming and optimal solution search heuristics are objective algorithms but since these rely entirely on deterministic input data and they use statistical simulations and/or calculus theory, they can overlook practical limitations or synergistic opportunities in the supply chain. While linear programming can analyze multiple constraints with numerous decision variables—it produces only one optimal result: the objective function. This becomes a problem if the first choice fails requiring additional fall-back alternatives.

In summary, there are many scientific methods available to solve logistics problems and they can be found in the literature. In fact, the authors in *Logistics Research* present novel techniques (sometimes with vastly different solutions to similar problems). Often the unique approaches are derived by transforming or integrating methods from other disciplines into logistics. On the other hand, emerging logistics techniques are not yet well accepted; "the existing research is situation specific and in part contradictory" [10]. Notwithstanding the question of relevancy to the operational task at hand, a critical point asserted here is that the requisite assumptions for applying specific scientific methods must be verified before the techniques are applied to the logistics problem.

Finally, the chosen scientific method must match the goals and data types. As a simply analogy, using a household thermometer will not be very effective in monitoring the temperature of coal in a coking oven, nor would a multivariate statistical regression analysis be practical for identifying popular logistics topics from managerial interviews. Likewise, goal achievement has to be objectively and appropriately measured with reliable scales and techniques. As Otto points out "using survey-based research designs results are often gathered from a Likert scale, which may cause problems regarding the constructs, measurement, and items" [10]. This means that certain types of data (nominal such as colors and ordinal such as priorities in particular) require specific techniques and have limited application in the scientific methods for logistics.

2.2 Empirical studies of applied novel logistics techniques

The generally accepted logistics techniques are well described in *Logistics Research*, such as economic order quantity estimation, project scheduling, discounted cash flow, and many other topics. Conversely out-of-the-ordinary unique applications of cross-disciplinary scientific techniques to logistics are less common which of course does not provide innovative ideas to the practitioners. Empirical logistical studies of mining operations are extremely scarce—thus the best source of operations research for mining managers may be in the relevant applied analysis of supply chain management and logistics flow.

Nevertheless several mining industry studies were identified that illustrate this gap in the literature. Gamache et al. [3] is a study that closely parallels the case study in this paper. They analyzed the effectiveness of operator driven load-haul-dump vehicles in an underground coal mine to optimize the master schedule (dispatching, routing and scheduling vehicles whenever they need to be assigned to a new ore vein or excavation activity). The mine used an enterprise system but apparently the problem was complex due to changing status of ore levels, underground traffic network congestion on single-lane and bidirectional road segments, and unique operational constraints such as position-dependence for loading and dumping the vehicles bucket. They solved the problem by writing a software program based on the shortest-path technique (from operations research). In their situation, the factors were deterministic, but it might have been interesting to consider probabilities such as traffic congestion.

In another coal mine study by Temeng et al. [12], they tackled the scheduling dispatch problem much differently—although it was a surface pit, their ideas could generalize to any complex logistics problem. They applied nonlinear goal programming theory to develop a software routine that maximized production (supply flow through the network in their case), subject to constraints which included maintaining ore quality characteristics. For example, in the coal mining industry you would not wish to have too high a level of ash ($\leq$15%), total moisture ($\leq$15%), sulfur ($\leq$1%), and volatile matter must be no more than 37% [13]. Theoretically (or at least from an operations research perspective), the real challenge that Temeng et al. overcame was to combine maximization and minimization objectives in the same algorithm, which required a nonlinear model with conditional programming.

On that topic, nonlinear goal programming was also applied in a coal mine study by Strang [14] which analyzed surface pits in Australia and Indonesia to match supply with international client demand (to generate electricity). The challenge in that case was applying deterministic parameters (logistics costs) with heuristics (managerial estimates), along with nonlinear constraints. Demand was nonlinear because at higher coal prices customers would switch to other suppliers. The goals were to maximize return on investment but also to minimize costs to customers. The unique aspect was that a calculus-based linear programming supply–demand simplex tabu was integrated with a nonlinear goal programming model, and this was developed in an open source spreadsheet application (which apparently the company could maintain themselves).

Finally, Surgul [7] studied logistics operations at an aggregate particle mine where he found bottlenecks and idle time wasted money when expensive equipment and/or engineers were underutilized. His approach was to use economic production quantity and queue theory (both from operations research), to quantify the delays, thereby illustrating the cost of underutilization. This is important research, not only due to his integrating two different theories related to logistics inventory replenishment, since productivity was quantified.

Outside the mining industry, there are numerous deterministic approaches applied for production planning logistics. Integer or linear programming are often used for logistics situations where constraints such as the cost as well as the number of trucks/ships and operators are known [15–17]. One of the most interesting examples of mixed integer and linear programming was the freight-inventory optimization study by Mendoza and Ventura [18]. In their model, they included weighted mean transportation costs with integer constraints for supplier selection and they used economic order quantity linear constraints as inventory replenishment objectives, while suggesting the use of spreadsheet software to work out the optimal solution. In another example, Chen and Askin [19] applied integer programming with net present value to optimize the portfolio selection of projects. Mathematical programming techniques are often applied to nonlinear, context-specific complex logistics, and paradoxical (NP-hard) situations where an optimal solution is difficult to identify [15, 20]. Markov chains and other general search techniques are widely used in operations research [21, 22].

Further to the above, function modeling has also been used as an optimization technique to solve logistics production problems [23, 24]. Supply–demand-flow approaches have been applied to solve routing and sequencing operational problems [23, 25, 26]. Petri nets and other nearest-neighbor heuristic-based search techniques could be considered a variant of flow analysis, which have also been used to solve logistics shortest-route problems e.g., [27]. Network queuing models were used to simulate a vehicle storage and retrieval system [28]. An innovative model was constructed by integrating queuing theory with the Analytical Hierarchy Process and Value Engineering [29]. This study uniquely proposed a scheduling solution for a mixed priority queue that did not rely on any traditional probability distribution.

Interestingly, several statistically oriented methods have been integrated with operations research techniques and applied for logistics analysis—such as the work of Kleijnen [30, 31]. Mixed-method (qualitative and quantitative data) techniques have been applied in recent studies. For example, Analytical Hierarchical Process was used to quantify subject matter expert opinions in nuclear projects [32]. In similar fashion, X-ray radiology criteria, in totally different base units, were converted to dimensionless weights for numeric comparison [33]. Finally, a well-known management science methodology, Quality Function Deployment, was integrated with brainstorming consensus making to estimate canonical rank coefficients to prioritize budget allocation for new product logistics [34].

Recent fascinating empirical logistics studies have begun to integrate scientific methods from the other disciplines and discuss critical assumptions for using certain techniques. Dragut and Bertrand [35] created an improved microlithography process for a new product development project based on a simple queuing model. They used general server queue models with engineering design tasks averages. What was insightful about their research was the application of the Kolmogorov–Smirnov goodness-of-fit test to show the model was statistically equivalent to several sets of experimental data gathered from the case study company. This goes beyond a conceptual queue model by proving a new design could produce the same result as existing production. Additionally, their data were not simulated, and in fact the purpose was to find an appropriate logistics model to analyze and solve their operational problems.

2.3 Synthesis of logistics literature review

In summary of the above literature review, it is obvious that many techniques exist to solve logistics problems. The important requirement argued here is to match the techniques with the organizational goal and data types. Of course the difficult task is selecting the best technique to solve a problem, and then ensuring it is valid for the situation. That is the goal of this study, to identify appropriate scientific methods to solve logistical problems at a mine, and then properly apply them for managerial decision-making purposes.

In his discussion of a framework for building a decision-making or logistics solution-valuation calculus, Otto points out that unless the parameters are deterministic, the operational logistics data must be first gathered. “The more difficult task is to locate, identify, collect, quantify, and verify cost and benefits” [10]. More so, as pointed out earlier, when using techniques from the other established disciplines, it is necessary to verify any assumptions before going further in the logistics analysis. The validation requirements will vary by the technique. These assumptions can be found in the literature which describes the technique. Statistical techniques, for example, have very rigorous requisites (primarily data type, sample size, distribution shape, and purpose). Many financial techniques employ the basic geometric weighted mean from statistics (this is the principle of compounding underlying all time value of money problems). Other management science techniques have their own requirements. In the case of most operations research techniques, usually it comes down to either maximization or minimization objectives, and linear versus nonlinear slopes representing the change relationships between variables (e.g., constraints). This will be explored in the next section.

3 Methods and case study

In terms of methods, Otto makes a good argument for the use of case studies in logistics research. “Assuming proper usage of the techniques to conduct empirical studies and leaving aside the idiosyncrasies of 'best practice' studies, the basic argument is that a network investment will pay off since it did in other companies" [10]. Thus, other researchers and practitioners could learn more from an applied study case such as this as compared to a wholly theoretical article (as would be the custom in pure mathematics and operations research).

Insightful authors point out that the logistics literature often overly focuses on assessing qualitative data, such as supply chain management relationships but fails to link "non-financial to financial indicators of firm value" [10]. Other researchers focus on the bottom line using traditional supply–demand and break-even analysis, such as Mendoza and Ventura [18]. However, most manuscripts discuss robust frameworks, empirical case studies of best practices, or optimal simulated models, but rarely do these grounded-theory and empirical-practice-based research philosophies merge in the same study.

Another problem with logistics studies (more specifically the operations research literature) is that while the prescribed models are powerful, they are often impractical for logistics managers to apply due to their complexity [36–41]. USA-based university MIT Professor John Little (well known for Little's Law [42]) complained: "managers don't understand the models" [40]. By this, he meant the interface is poor and the variables are difficult to apply to operations data. Therefore, logistics studies should explain and apply the models in a way that everyday operations managers can understand, in addition to the aforementioned requirements of linking qualitative priorities to quantitative bottom line financial performance measures.

In answer to the above call for better logistics research methods, the case study methodology is applied using the ideas of Yin [43] and Creswell and Tashakkori [44]. A USA-based coal mine is used to demonstrate how a mixed-method logistics model can be created in spreadsheet software, in a way that operations managers can understand the model and apply it to production data.

3.1 Case study participants

Barton Mines is privately held mining company founded in 1878 at Warrensburg NY, USA. The plant is beside the North Hudson River in the Adirondack Mountains of NY. Barton primarily mines and mills the garnet crystalline into abrasives (http://www.barton.com). They are well known in the world for sand paper and sand blasting materials, mainly due to the sharp edges of the crystals and dust-free residue (less than 1% silica). A resource-based competitive advantage is that the abrasive crystals are durable so they can be "reused" multiple times. Their main resource is a hard rock garnet crystal, which they mine and mill for diverse applications such as water-jet cutting, blasting, bonded/coated abrasives and specialty lapping/grinding media (e.g., drilling heads). They extract crystalline hard rock ore from their open surface pit in Warrensburg (and occasionally purchase it), transport it through a multistage milling process to crush, separate the pieces, and refine the concentrate into purity grades grouped by crystal density (customized for particular industrial uses).

Barton has diversified horizontally (making abrasive bonded products), vertically (producing sand blasting equipment under OEM licenses), and reverse supply chain engineering (acquiring sources and transportation). Their competitive advantage consists of garnet crystal milling know-how, reputation for high quality abrasive concentrate, on-time delivery, and convenient local inventory of related sand blasting equipment (with spare parts). Additionally, they have access to crystalline supply, their plant is located beside a renewable water supply (needed for milling), a rail line runs beside their plant, and the Interstate-87 is about 30 miles to the east.

3.2 Case study problem

The company refines garnet crystal from their open pits (surface mining) in the mountains. They use planning software that employs simulation to predict operations requirements. They also use various financial and statistical techniques including forecasting to manage and control critical operational processes. They have an enterprise system that handles the corporate financials (general ledger and so on), and a small system for human resource management.

One issue that has arisen in USA is the frequency and severity of mining accidents, such as the recent tragedy in West Virginia [45]. Accidents and injuries are often due to congestion at mine service queues and along haul routes. The US Bureau of Mines Studies (http://www.archives.gov) reported the following surface mine accidents (1994–2000), which are higher per capita for surface mines (as compared to underground mining):

- 4,397 haulage accidents; 1,300 truck accidents;
- 640 truck accident traumatic injuries; 232 surface fatalities v. 358 all mines;
- 232/358 = 65% fatalities involve (the small population of) surface mines.

An objective in the case study project is to analyze and improve operations at the refinery. The refinery gets its supply from the open pits through off-road trucks. They wish to know if more loading ramps near the refinery conveyor system would improve productivity. The cost of a truck operator, fuel, and other related expenses (including oil and maintenance) averaged $45 per hour in the last 12 months. It is too hazardous to drive at night and due to safety requirements, so all operational staff report for a common daytime 8-h shift (administration and management work other hours). Thus far it has been management-by-exception, allowing trucks to arrive and dump when ready, letting operators work a normal 8 h shift, and assuming that there are no delays or underutilization. Inventory tends to be low and since the company bases its reputation on not being out of supply, they want to ensure that does not occur for any clients. They could hire more drivers (as they have access to additional trucks in Glens Falls) and/or they could easily build another loading ramp at an estimated cost of $5,000.

4 Analysis and discussion

The first step in this project was to gather the parameters. According to the existing planning manuals, the expected time for a Caterpillar 793C (off-road highway truck) to bring the load into the refinery are and into position to dump on the conveyor is 7.92 min (Caterpillar 2003). The dumping process is relatively quick (2.51 min on average), requiring only positioning, pausing the conveyor belt, dumping, and restarting the belt, while the truck leaves. However, their trucks have not been anywhere close to these averages (according to company estimates the trucks arrive faster and take slightly longer to dump).

A frequency distribution was calculated from the last 12 months historical data, by counting how many of their trucks had arrived during each minute at the refinery (it took all trucks only 7 min at the most to get there). Based on the history, no trucks had arrived in less than a minute, only 1% arrived in a 1 min interval, 22% in the next 2 min interval, 25% in the next minute interval, followed by 19, 15, and 12%, and 5% during minute intervals 3–6, with the remaining 1% of trucks arriving in the 7th minute. This data was measured by RFID so each truck can be recognized independently and not counted twice. Thus, it looked like their trucks were performing 131% better than the planning specifications indicated (if their average is used as the base).

However, their mean fleet performance dumping loads at the refinery was worse compared to the expectation of 2.51, averaging 3.66 min. This high level benchmarking process using statistical averages pinpointed where the main problem might be—near the refinery itself. It was first proposed to use comparative statistical t tests to determine if what they were experiencing was significantly different than expectations and if not to calculate forecasts and linear regression to predict if more trucks and/or loading ramps could be added to the configuration so as to improve performance. If they were to continue to apply parametric statistical theory they would need to test the assumptions that the historical data approximates a normal distribution and then calculate various estimates of central tendency such as standard deviation, and comparative measures such as z-scores and t tests. Following that, the team could use exponential forecasting to predict truck arrival and dumping times. Additionally, it may be possible to develop cause-effect predictions using linear regression.

It is necessary to verify the “normality” of the data before using parametric statistical techniques [46]. This was achieved by using two statistical techniques: the Anderson–Darling test for normality (AD-test) and secondly the Kolmogorov–Smirnov test (KS-test) which is a nonparametric version using a chi-square matrix [47]. The formula for the AD-test is:

$$\sum_{i=1}^{N} \frac{(2i-1)}{N}\left[1nF(Y_i) + 1n(1 - F(Y_{N+1-i}))\right]. \qquad (1)$$

In the above formula, N is the degree of freedom, n is the number of observations, i is the ordered interval from low to high, F is the cumulative distribution frequency for Yi (ordered data points).

4.1 Failure of preliminary test and experiment redesign

The results were that unfortunately both tests failed—the historical data did not approximate a normal distribution. This is likely due to the fact that mining trucks and refinery systems do not follow the normal “bell curve” and instead approximate other distributions such as Weibull, Triangular, Poisson, Exponential, Erlang, and so on. Although this shuts the door on numerous parametric techniques, usually every data set follows some pattern which can be analyzed. In fact, it was pointed out earlier that Dragut and Bertrand [35] used nonparametric KS-tests with queue models (which use waiting line theory from operations research).

Since the above tests failed, a new approach was needed. As per above, it seems that queue models may be more applicable. Queue models are based on waiting line principles (such as tellers in banks, except that here it will be trucks at refineries). A key principle in queue models is Little’s Law which states that the total length of the system equals the arrival rate per specified interval (known as Lambda λ) multiplied by the mean time an object spends in the system; thus the formula for total queue length is [42]:

$$L = \lambda * W. \qquad (2)$$

Another important parameter is the average utilization which refers to the probability the system is busy (active). Utilization is generally calculated as the arrival rate Lambda λ divided by the service rate μ; statistically this is the complement of being idle, or in short format:

$$U = 1 - P(0) = \lambda/\mu. \qquad (3)$$

The remaining key variables refer to the length of the service queue or number of objects waiting in the service queue (Lq), and the mean time waiting in the service queue (Wq). The difference between W and Wq is that the latter are a subset of the former time in the system (in the waiting queue itself), while in similar principle, L represents the total length of the system and Lq is the (shorter) time-length of the queue within L. As noted above, the probability the system is idle or not busy is $P(0)$ which refers to the probability of zero objects in the system (the mutually exclusive complement of busy). These parameters can be estimated for a refinery and then multiplied by cost coefficients to evaluate the productivity and cost-benefit of improvements.

There are numerous queue models in the literature. The four main components are: input (arrival), waiting (queue), process (servers), and (output service). The literature differs on which distribution models to assume for the arrival and service components, along with how many servers. The characteristics of the case study can limit the search for a model. Since the company has extra trucks and only one refinery (server) it is convenient to select a simpler queue model. The M/S/1 model is the most common as it is simple and often represents many waiting line situations; it has a single server, a Poisson arrival rate, and an exponential service rate. The M/D/1 model also uses a single server, a Poisson arrival rate, but expects a constant/deterministic service rate (such as a conveyor system—which sounds promising to apply to this case). Finally, the M/M/s is a multiple server format, expecting Poisson arrivals, and exponential service times. Note M/M/s model behaves identically to M/S/1 is it uses one server so we can overlook M/S/1 to make things simpler. Additional basic queue models not tested here but useful for others to consider are: M/G/1 (single server, Poisson arrivals with average population service times); and M/M/f (multiple servers, Poisson arrivals, exponential service times with finite population sizes). There are additional variations of queue models beyond the scope of this case study. For example, more variations simply use other underlying distributions and/or buffers.

This analysis can proceed using M/D/1 and M/M/s queue models. Back to the drawing board, it is again necessary to test the production data to ensure it would fit these models. Both expect a Poisson arrival distribution, but M/M/s (and M/S/1) expect an exponential service distribution, while M/D/1 expect a constant service rate. Validating Poisson, Exponential and Constant distributions requires special tests—normal parametric techniques cannot be used. Although Dragut and Bertrand [35] used the KS-test, a simpler but equally effective nonparametric goodness of fit test (GF-test) can be used to compare distribution characteristics, based on the chi-square formula [46]. This is widely available in statistics text books. The GF-test formula is:

$$\chi^2 = \sum_{i=1}^{k} \frac{(A_i - E_i)^2}{E_i}; \tag{4}$$

where $\chi^2 =$ chi-square estimate (smaller values mean more similar distributions), k is the sample size, A_i is the actual probability of an observation, and E_i is the expected probability of the observation.

4.2 Testing Poisson arrival intervals for a queue model

The previous historical data can be salvaged to create these estimates. The actual arrival probabilities can be calculated by counting the trucks which had arrived in each minute interval (0–10). However, since management feels productivity has changed, a new sample was taken by observing how many trucks arrived in a typical busy shift ($n = 140$), tallied in 1 min intervals. The results are summarized below in Table 1 (for now ignore the GF-test data at the bottom).

Here, the historical cumulative probability distribution function (CPDF) is shown at the left, followed by 1-min time intervals (X), then the historical (1 year) probabilities. The next three columns show the actual count in a 1-h observation sample frame, with the calculated probability (X/sum(X)). The mean of a Poisson distribution is known as the expected value:

$$\mu = \sum_{x} xP(x); \tag{5}$$

where x is the count(x) per X interval, multiplied by $P(x)$ which is the probability estimated by the count(x) divided by the total sample size (140 in this sample), all of which are summed to form the average

The Lambda λ is equal to the mean (μ), which from Table 1, is 2.58 for the sample, and 2.86 for the historical data. The first question that arises goes to whether this historical data and the sample data are "normal for Poisson distributions". This can be tested by creating a "Poisson expected" distribution using the long run historical $\lambda = 2.86$ as the parameter for the function to forecast a probability in each time interval, using the formula:

$$P(x) = \frac{e^{-\lambda} * \lambda^x}{x!}; \tag{6}$$

where $e = 2.71828$, x is the time interval, and $x!$ is the factorial of x.

A bivariate plot was created (as shown in Fig. 1) to graphically depict the shape of the sample arrival data as compared with a calculated Poisson expected distribution using Eq. 6. Following this, two GF-tests were applied: the first to test hypothesis 1 that the historical data would fit a

Table 1 Historical and sample refinery data to verify Poisson arrival distribution

Arrival distribution (number of trucks entering refinery at 1 h time interval X)

Historical CPDF	Historical interval X	Historical interval $P(X)$	Historical $P(X)*X$	Actual Count (x)	Actual $P(X)$	Actual $P(X)*X$	Poisson Expected	Chi-square Actt. versus exp.
0.00	0	0.01	0.00	4	0.0286	0.00	0.0758823	0.0294973
0.01	1	0.22	0.22	30	0.2143	0.21	0.195668	0.0017715
0.23	2	0.25	0.50	42	0.3	0.60	0.252272	0.0090298
0.48	3	0.19	0.57	30	0.2143	0.64	0.2168338	2.994E-05
0.67	4	0.15	0.60	17	0.1214	0.49	0.1397803	0.0024094
0.82	5	0.12	0.60	13	0.0929	0.46	0.0720867	0.0059846
0.94	6	0.05	0.30	4	0.0286	0.17	0.0309801	0.0001873
0.99	7	0.01	0.07	0	0	0.00	0.0114121	0.0114121
1.00	8	0	0.00	0	0	0.00	0.0036784	0.0036784
	9	0	0.00	0	0	0.00	0.0010539	0.0010539
	10	0	0.00	0	0	0.00	0.0002717	0.0002717
	Total	1.00	2.86	140.00	1.00	2.58	1.00	0.07
Goodness of fit hypothesis tests				H1: historical <> actual?			H2: actual <> expected?	
Significance level		0.01	$\chi^2 p$	1.00000	No. sig. dif.		1.00000	No. sig. dif.

Poisson distribution, and the second to assess hypothesis 2 that the recent sample would also be similar to a Poisson distribution. Equation 4 was applied for both GF-tests (using a confidence level of 99%, which is a significance level of 1%). Both of these passed the KS-tests (with a high probability value indicating both distributions being compared are not significantly different) as summarized at the bottom of Table 1. An example worked-out chi-square is shown in the last column of Table 1 ($\chi^2 = 0.07$) which compared the sample observation to an expected Poisson distribution. At this point, we can conclude the mining company truck and refinery operation data approximates a Poisson distribution which can be modeled as an arrival queue.

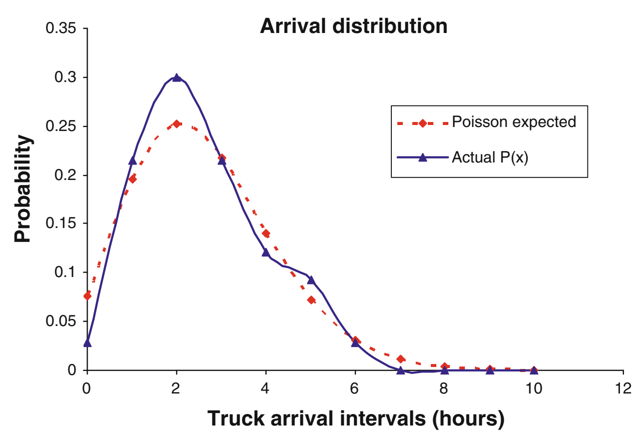

Fig. 1 Mine refinery sample arrivals compared with Poisson expected distribution

4.3 Testing exponential service durations for a queue model

Next, the refinery service rates need to be tested as an Exponential distribution. The service rates can be calculated from the history data, grouping the time durations into 1-min intervals to generate a frequency count. Since the service times were continuous data (each truck had slightly different minutes and seconds), it is customary practice to arrange ratio data types into a histogram using intervals. Here, 1-min service intervals were used for the durations (0–0.99 s, 1–1.99 s and so on). As a side note, any interval could be used but a 1-min interval is commonly used in mining and it is convenient and applicable in the operations here (hours would generate too much data just to measure the same effect). The results are summarized below in Table 2.

Table 2 is arranged like Table 1, except as noted the X is duration intervals, The $P(x)$ represents the historical 12-month data probabilities. The $P(X)*x$ column is used to calculate the expected value or mean (μ), which here was 3.66 for the historical, and 3.76 for the actual. The λ of an exponential distribution is the reciprocal of the μ which is $1/3.66 = 0.273224044$ (for history data), and $1/3.76 = 0.272223419$ (for the sample). The Exponential expected distribution can be created based on the historical λ, using the formula:

$$f(x) = \lambda e^{-\lambda x}; \tag{7}$$

Table 2 Historical and sample refinery data to verify Exponential service distribution

Service distribution (duration in X minutes between truck arriving, dumping, and leaving)								
Historical	Historical duration		Historical	Actual	Actual	Actual	Exponential	Chi-square
CPDF	X	$P(X)$	$P(X)*X$	Count (x)	$P(X)$	$P(X)*X$	Expected	Act. versus exp.
0.00	0.99	0.19	0.19	24	0.1727	0.17	0.2084711	0.006151
0.19	1.99	0.20	0.40	30	0.2158	0.43	0.1586303	0.0206234
0.39	2.99	0.15	0.45	20	0.1439	0.43	0.1207053	0.0044513
0.54	3.99	0.13	0.52	18	0.1295	0.52	0.0918474	0.0154327
0.67	4.99	0.11	0.55	15	0.1079	0.54	0.0698887	0.0206886
0.78	5.99	0.08	0.48	15	0.1079	0.65	0.0531799	0.0563331
0.86	6.99	0.04	0.28	5	0.036	0.25	0.0404658	0.0004992
0.90	7.99	0.10	0.80	12	0.0863	0.69	0.0307913	0.1001793
1.00	8.99	0	0.00	0	0	0.00	0.0234298	0.0234298
	9.99	0	0.00	0	0	0.00	0.0178282	0.0178282
	10.99	0	0.00	0	0	0.00	0.0135659	0.0135659
	Total	1.00	3.66	139.00	1.00	3.67	0.83	0.28
Goodness of fit hypothesis tests				H1: historical <> actual?			H2: actual <> expected?	
Significance level		0.01	$\chi^2 p$	1.00000	No. sig. dif.		1.00000	No. sig. dif.

where e and the other factors are the same as in the Poisson formula.

Note that the Lambda λ is the mean number of occurrences per unit time, x is the number of time units until the next occurrence (this is duration). In theory, the λ of a Poisson distribution (for the same measure) is an inverse function of the same unit from a corresponding Exponential distribution, meaning that a Poisson distribution $\lambda = 1/\lambda$ for the same Exponential distribution mean. However, that does not mean that the two tables here are corresponding because they measure different things (arriving and then getting service at the refinery); instead this theory means that a Poisson distribution of the service would have a λ that is the inverse of the Exponential distribution

$$1/\mu \tag{8}$$

for the same service component.

Equation in 7 was applied to create the Exponential expected distribution. Another bivariate plot was created (see Fig. 2) to graphically illustrate the difference (and similarity) between the refinery service rate sample as compared to the Exponential expected distribution. It is obvious in Fig. 2 that the trend lines are not exactly identical, so more precise techniques are needed to judge if the two shapes are statistically similar—using the GF-tests.

Next, two more hypothesis were tested, H3 to verify the historical service rate data could approximate an Exponential distribution, and H4 to do likewise with the new sample data. Both GF-tests confirmed the history data and sample service rates approximated an Exponential distribution, as shown as the bottom of Table 2. One slight

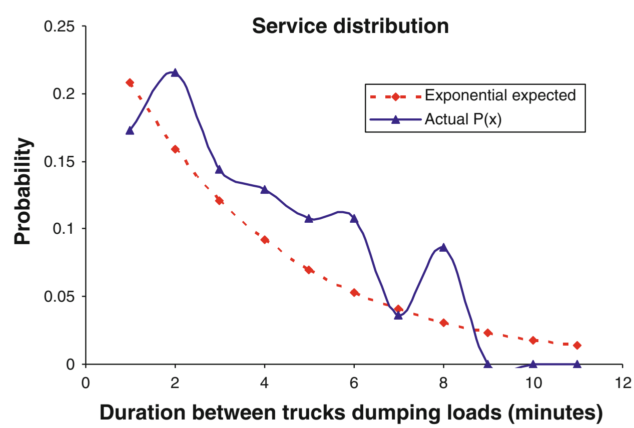

Fig. 2 Mine refinery sample service rates compared with Exponential expected distribution

anomaly in Table 2 is that there are only 139 of the 140 truck observations in the sample, which meant that the one remaining truck had not yet returned during the timed experimental frame. This did not impact the statistical significance. Thus, at this point all four hypothesis are accepted that the historical and sample data can approximate a Poisson distribution (for arrivals) and an Exponential distribution (for service rates), respectively, for use in a queue model.

4.4 Building an M/M/s queue model

The visual distribution shape in the graphs (Figs. 1, 2), and the results of the GF-tests, confirm the data do approximate a Poisson distribution for arrivals, as well as an Exponential distribution for service rates. This would fit well with an M/M/s queue model. Therefore, it would not be logical to start testing an M/D/1 queue if it requires a constant service rate when we have just verified the service rates approximate an Exponential distribution. It should be noted though that there is a technique in the literature that one may use to create an expected constant distribution as this would be unimodal (all means and λ are the same). The uniform distribution has an expected value probability of

$$1/\min(x) + \max(x) \tag{9}$$

where the minimum and maximum are the smallest and largest observations. It is not necessary to perform a KS-test on this because a straight horizontal line from a uniform distribution will not resemble an Exponential distribution.

At this point, the objective is to build an M/M/s queue model for the sample refinery data. The reason the sample is being used instead of the historical data is that we have already verified that the arrival and service rate distributions are statistical similar between the 12-month history and sample. We wish to use the sample because it is more recent and will depict the newest trends. Also, since the objective is to help the case study company improve productivity at the refinery, we will use the \$45 truck cost and \$5,000 service ramp estimates to build a break-even model integrated to the M/M/s queue model to solve this problem.

The calculations for an M/M/s queue model must use rates that are in the same units expressed as an interval (not duration). Therefore, the Poisson λ can be used but the Exponential μ must be converted to an interval (Eq. 8) by taking its reciprocal (which is $1/\mu$ or $1/\lambda$). First, a graphical interpretation of the completed M/M/s model is shown in Fig. 3, which will help to explain it (below that).

As noted, the sample arrival rate λ was taken from Table 1 ($\lambda = 2.57857$) and μ was drawn from the mean sample service in Table 2 as $1/\mu$ (which was shown in Table 2 already converted to $\lambda = 3.6735$). The server idle probability formula is:

$$P_O = \left[\sum_{n=0}^{1} \frac{(\lambda/\mu)^n}{n!} + \frac{(\lambda/\mu)^s}{s!}\left(\frac{1}{1-\rho}\right)\right]^{-1}; \tag{10}$$

where $n = 0$ and $s =$ servers, $p = \lambda/2\mu$. From the above, the queue system utilization (busy state)

$$P_w = 1 - P_0; \tag{11}$$

the average waiting time in queue

$$W_q = \frac{L_q}{\lambda}; \tag{12}$$

the total waiting time (arrival and in queue)

$$W = (1/\mu) + W_q; \tag{13}$$

the length of the queue (number of trucks in wait mode)

$$L_q = \frac{P_o\left(\frac{\lambda}{\mu}\right)^s \rho}{s!(1-\rho)^2}; \tag{14}$$

the total length of the system (trucks arriving + waiting)

$$L = (\lambda/\mu) + Lq. \tag{15}$$

The interpretation of the M/M/s queue model in Fig. 3 is that the refinery is busy approximately 70% of the time (idle the other 30%). There is an average of 1.6532 trucks in the refinery queue (waiting in the ramp area), out of an average of 2.3551 trucks arriving, waiting and dumping their loads. The average time waiting in the queue is 0.6411 min (slightly more than half a minute)—this is a key productivity lost indicator. The average time for trucks to be in the system (arriving, waiting, and dumping) is 0.9133 min (about 1 min).

4.4.1 *Cost-benefit and break-even scenario analysis*

In reflecting on the M/M/s queue model (from Fig. 3), since the utilization is approximately 70%, this means that the truck drivers could be idle on average for 30% of the time (remember the arrival rates indicated when they were driving to the refinery, when they are waiting, and when they are dumping the loads). Certainly, we would allow a lunch period and breaks but for planning purposes more time is added to the day to include that so as to get 8 h of work per day (the operators are paid a good wage of close to \$360 per day which is approximately a \$79,000 salary, to cover this).

Fig. 3 M/M/s queue model with 1 server for refinery operations

Queues	**Model: M/M/s (exponential service times with multiple servers)**			
Queue input data		arrivals & service	**Queue model operating estimates**	minutes
Arrival rate (λ)	2.5786	Arrivals/minutes	Average server utilization (P_w)	**0.7019**
Service rate (μ)	3.6735	Finished/minutes	Average number of customers in the queue (L_q)	**1.6532**
Servers (s)	1		Average number of customers in the system (L)	2.3551
Mean arrival rate (λ), mean service rate (μ); rates same units; service rate > arrival rate: μ x s > λ			Average waiting time in the queue (W_q)	**0.6411**
			Average time in the system (W)	0.9133
Unit of measure:	minutes	8 hours/shift	Probability (% of time) system is empty (P_0)	0.2981
Cost 29 staff @ \$45/shift	\$10,440	x 29 truck drivers	Daily cost * idle time P_0 = cost productivity lost	**\$3,112**

One way of applying this productivity as a cost-benefit is to consider that idle time as productivity lost (time paid for but not utilized since the drivers are waiting at the refinery to dump the load). Thus, using the \$45 wage $\times$ 8 shift hours $\times$ 29 operators $\times$ 29.81 = \$3,112 lost per day. If this were extended for the 220 planned operating days, this would be \$684,566.91 lost per year.

Now, we can use the same M/M/s queue model to perform what if scenario analysis to determine if the utilization could be improved by building another ramp at the refinery. The results of adding a second server are shown in Fig. 4.

If is obvious from the revised model in Fig. 4 that the productivity lost is actually higher with two server ramps since utilization dropped from 70 to 35%, and idle time increased from 30 to 48%. The additional cost of this is \$5,015 – \$3,112 = \$1,904 per day. This is not a good alternative since it would also cost \$5,000 to build the extra ramp. In inferential implication from the M/M/s (with an additional server) would be that adding a second ramp would only cause more trucks to wait in the queue.

In looking at the basic M/M/s queue formula for utilization, which in simplified form is $\lambda/(\mu \times s)$, from a mathematical perspective, the arrival rate needs to be increased or the service rate decreased (the latter of which makes no sense to decrease the refinery efficiency). Thus to improve productivity, in a deductive sense, the company must increase the arrival rate. If the company is able to invest the \$5,000 into improving the road to the refinery by making it wider with more than two lanes, this is estimated (by manager heuristics) to increase the arrival rate by 10%. Thus, the $\lambda = 2.5786 \times 1.1 = 2.8364$ for arrivals. Now, when the M/M/s model is recalculated with this new λ, the utilization is much better, as shown in Fig. 5—this is a predictive forecast (not empirical).

From the forecasted M/M/s model shown in Fig. 5, it can be seen that the 10% increase in arrival queue mean interval rate has produced a 7% increase in utilization from 70 to 77%, which resulted in a daily cost reduction of \$733 down to \$2,379, or a yearly cost of \$523,343.60 (productivity lost). It is easy to see that \$161,223.31 could be saved in a year. The break-even formula can indicate how long it would take to pay back the \$5,000 investment, which when divided by the \$733 savings per day, results in 6.82 (about 7) days.

The next step with this case study project is to investigate how realistic it is to improve the roads, or perhaps find another approach to increase the arrival times. This (as with the managerial heuristics) requires qualitative data, which is best done by arranging a subject matter expert brainstorming session so that other alternative ideas can be generated to see how the arrival rates can be improved. For example, it may be possible to reengineer the operational processes, such as working staggered shifts over longer days, to increase arrival rates, putting less traffic congestion on the rough roads, and without increasing labor costs.

5 Conclusions

The case study successfully demonstrated how to locate and apply better (and proven) techniques to verify hidden assumptions and solve contemporary logistics problems at a surface crystal mine refinery. The company wanted to improve productivity at the refinery to meet or exceed inventory demand. In the past, they had been using forecasting along with economic order quantity inventory planning. Human resource scheduling was done by the human resources department. The problem was accidents had increased and the existing logistics analysis tools could not identify how to improve productivity at the refinery.

The logistics analysis started with testing the "normalcy" of historical operations data from RFID-equipped off-road trucks arriving and dumping their loads at the refinery. In this way, the team hoped to use exponential forecasting and possibly multivariate regression to improve the arrival and service rates. When the initial tests failed, the team went back to the drawing board and selected nonparametric statistical tests. Since the inventory problem actually centered on the refinery congestion, waiting line principles were researched and a queue model was built to link truck arrival rates with servers (refinery ramps) and the dumping service durations at the conveyor. An M/M/s queue model was selected (over others which were ruled out for various mathematical or practical reasons). The M/M/s was ideal for the analysis task because it could

Fig. 4 M/M/s queue model with 2 servers for refinery operations

Queues	Model: M/M/s (exponential service times with multiple servers)			
Queue input data		arrivals & service	**Queue model operating estimates**	minutes
Arrival rate (λ)	2.5786	Arrivals/minutes	Average server utilization (P_w)	**0.3510**
Service rate (μ)	3.6735	Finished/minutes	Average number of customers in the queue (L_q)	**0.0986**
Servers (s)	2		Average number of customers in the system (L)	0.8006
Mean arrival rate (λ), mean service rate (μ); rates same units; service rate > arrival rate: $\mu \times s > \lambda$			Average waiting time in the queue (W_q)	**0.0382**
			Average time in the system (W)	0.3105
Unit of measure:	minutes	8 hours/shift	Probability (% of time) system is empty (P_0)	0.4804
Cost 29 staff @ \$45/shift	\$10,440	x 29 truck drivers	Daily cost * idle time P_0 = cost productivity lost	**\$5,016**

Fig. 5 M/M/s queue model with 2 servers for refinery operations

Queues	Model: M/M/s (exponential service times with multiple servers)			
Queue input data		arrivals & service	**Queue model operating estimates**	minutes
Arrival rate (λ)	2.8364	Arrivals/minutes	Average server utilization (P_w)	**0.7721**
Service rate (μ)	3.6735	Finished/minutes	Average number of customers in the queue (L_q)	**2.6166**
Servers (s)	1		Average number of customers in the system (L)	3.3887
Mean arrival rate (λ), mean service rate (μ); rates same units; service rate > arrival rate: μ x s > λ			Average waiting time in the queue (W_q)	**0.9225**
			Average time in the system (W)	1.1947
Unit of measure:	minutes	8 hours/shift	Probability (% of time) system is empty (P_0)	0.2279
Cost 29 staff @ $45/shift	$10,440	x 29 truck drivers	Daily cost * idle time P_0 = cost productivity lost	**$2,379**

handle one or more servers while relying on Poisson arrivals and exponential service times.

The historical data was validated (using chi-square tests) to verify the truck arrivals approximated a Poisson distribution, and likewise, to ensure the dumping service durations were similar to an Exponential distribution. An empirical sample was taken from operations during a busy shift ($n = 140$), to observe current trends. This sample was also verified to approximate a Poisson distribution for arrive intervals as well as an Exponential distribution for service duration. From this, a M/M/s model was calculated to reveal refinery utilization was 70%, which meant it was idle 30% of the time. Break-even cost-benefit analysis estimated a productivity loss of $3,112 lost per day which was extrapolated to equal a $684,566.91 loss per year.

Scenario analysis was applied to generate alternative M/M/s solutions. By examining the underlying queue formulas and considering the goals of the case study, it was determined that the best strategy would be to increase the arrival rates. The M/M/s model was used to simulate this, which predicted a 7% increase in utilization to 77% (from a 10% increase in arrival rate), projecting a $733 daily cost reduction, which was a net savings of $161,223.31 per year. Break-even analysis indicated it would take only about 7 days of operations to pay back a $5,000 road-improvement investment necessary to increase arrival rates.

Despite the fact that preliminary parametric tests failed, the team practiced thinking outside the box to design a new experimental framework using techniques from outside the logistics discipline. From that brainstorming session, a multiple server queue model was developed by integrating nonparametric techniques, waiting line theory, stochastic probabilities, and break-even scenario analysis. The historical operations and sample test data were then used to analyze the existing refinery productivity, and to simulate an improved model. Qualitative data was also gathered from mining subject matter expects as input to the model. A practical solution was developed as a result of using mixed-method techniques.

By way of implications, this paper demonstrated how to use a case study with cross-disciplinary mixed methods applied to logistics analysis. Improving research methodologies in the logistics discipline was another underlying goal of the study. Practitioners have links (citations) to the technique sources and new models to explore. At a higher level, this paper put a new perspective to traditional logistics research, by purposefully researching the related disciplines for solutions to everyday operational problems (beyond the popular mathematical programming or "black box" commercial software "easy choices").

At the practical level, this paper demonstrated how to find logistics methods and how to apply parametric and nonparametric techniques to validate assumptions. These prerequisites are very frequently overlooked in the literature, but what can happen is that a totally invalid model can be developed which will produce invalid estimates (the old axiom "garbage in garbage out" would apply). Furthermore, the paper uniquely demonstrated how to redesign experiments when tests fail, and where to look for more techniques outside the logistics discipline.

Another positive benefit of this study is that since it focused on demonstrating proven techniques, there are no limitations per se except to advise other researchers and practitioners to select and properly apply methods (including any prerequisite validation) to solve logistics problems. Finally, while the case study company has solved their logistics problem of improving productivity at the refinery (using mixed-method techniques), the issue about improving safety (reducing accidents) is still unresolved, and is thus a recommended topic for future logistics research in the mining industry.

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