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AN EVALUATION AND FORECASTING MODEL FOR METAL-NONMETAL MINING RESEARCH NEEDS: MODEL DEVELOPMENT FOR COMPUTER-ASSISTED TECHNOLOGY

By John J. McClelland,[1] James P. Rider,[2] Julie Mitchell-Dubaniewicz,[3]
and George H. Schnakenberg, Jr.[4]

ABSTRACT

The U.S. Bureau of Mines formed a team in 1991 to begin developing a long-range research plan for computer-assisted mining that would benefit the metal-nonmetal mining industry. This report details the team's accomplishments, specifically, the development of a model that identifies metal-nonmetal mining research needs that could be addressed by the application of automation technology. The report also provides a summary of automation needs and applications based on visits with mining company representatives. The status and future direction of this work is also presented.

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INTRODUCTION

In 1990, the U.S. Bureau of Mines (USBM) initiated a project to evaluate mining research needs. Initial efforts focused on identifying the mining automation needs for metal-nonmetal (MNM) mines. The applicability of automation technology to the MNM mining industry was studied to identify equipment and tasks that, if automated, would increase safety and productivity. Study results formed the basis for developing a long-range plan for MNM computer-assisted mining research.

Following this effort, the USBM's Washington Office (WO) developed a logic diagram showing the necessary input for making qualified and informed decisions in assessing the mineral industry's mining automation needs (fig. 1). The diagram was to serve as a guideline for assessing automation needs and, more importantly, to provide a mechanism for rationalizing program research. It was obvious from the diagram that input would be needed from many areas of expertise within the USBM.

In 1991, a team of 20 volunteers from 4 of the USBM's research centers, the WO, and the Division of Information and Analysis (I&A) was formed to meet this challenge. The team's original intent was to devise a long-range plan for applying automation technologies to equipment used in MNM mining that paralleled the successful long-range plan for research on computer-assisted mining for coal. Because fiscal limitations would prevent the USBM from conducting research on all types of mining equipment used in the MNM industry, the team developed a scheme to select one type. The selection was based on how much industry would benefit from applying computer-assisted operation technology to the chosen type of equipment. Benefits would be measured by the improvement in worker health and safety, productivity, and by the impact on the mineral industry as a whole. Thus, the selected equipment would have the largest combination of (1) frequency of use in mining operations for a commodity of significant economic value, (2) prevalence of health and safety hazards, (3) high labor costs, and (4) how easily the research could develop and apply computer-assisted technologies.

This report presents USBM efforts to assess the health, safety, and productivity needs of the MNM mining industry for developing a long-range plan of research for computer-assisted mining. These efforts were successful in that the equipment identified was the same that industry felt was an issue. The USBM is now attempting to expand upon the initial effort by studying their research programs overall. These future research evaluation efforts are not within the scope of this report and will be reported on as research continues.

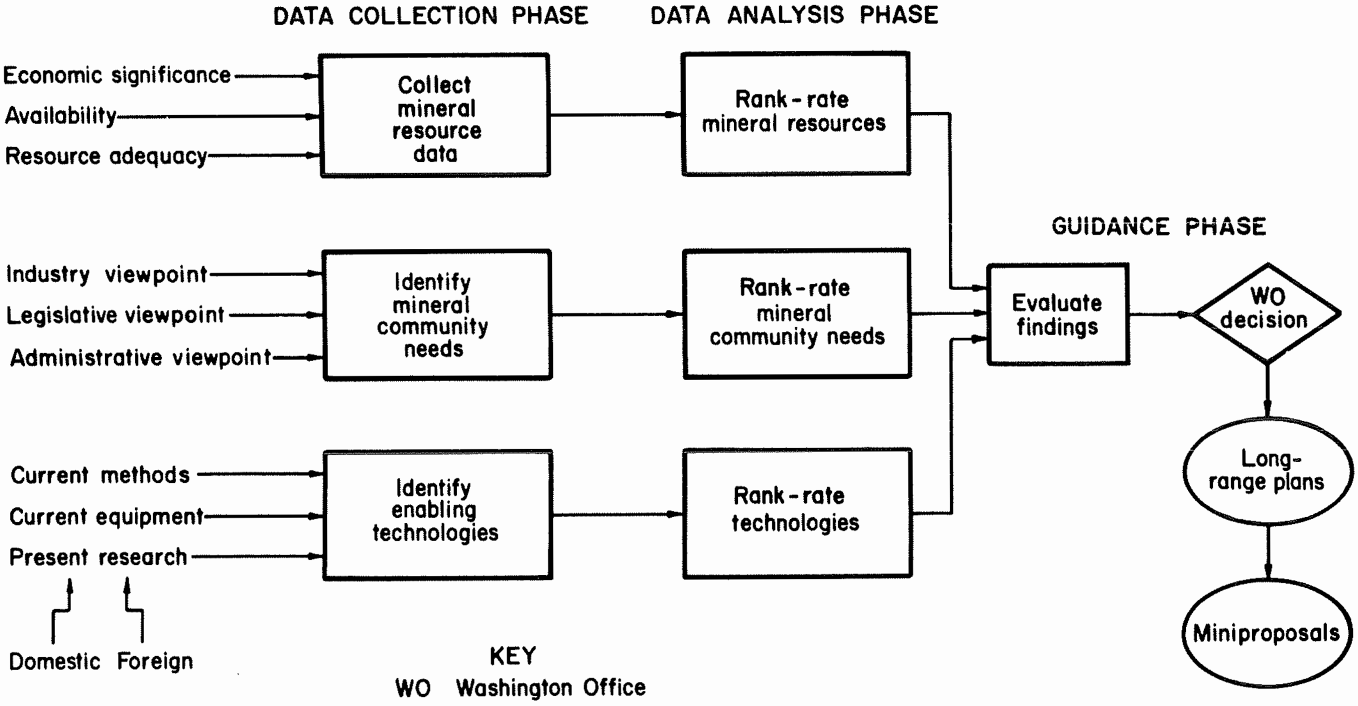

Figure 1.—Decision strategy for MNM, computer-assisted mining research.

ACKNOWLEDGMENTS

The authors wish to thank team members from the Denver, CO, Spokane, WA, Twin Cities, MN, and Pittsburgh, PA, Research Centers, USBM; the Division of Information and Analysis personnel, USBM, Washington, DC; and the Minerals Availability Field Office, USBM Denver, CO; for assistance in collecting data and developing the model.

APPROACH

Unlike the coal industry in which there is a single commodity, only two major underground mining methods, and a few types of mechanized mining equipment; the MNM mining industry produces at least 100 commodities of varying strategic and economic value and annual tonnage using a preponderance of mining methods dictated by the geometry of ore deposits and with a large complement of equipment types and applications. Without a quantitative assessment process, it is too overwhelming a task to objectively select and justify a research target for MNM computer-assisted technology that would produce the greatest benefit to industry per research dollar. Therefore, an assessment process was developed and modeled that minimized subjectivity and provided structure to the decision process so that a traceable path of reasoning could be maintained and defended. Three areas of investigation arose from this project: commodity statistics that enable judgment of its relative value; commodity producers (mines), ore deposit geometry, mining methods, and equipment usages; and health, safety, and labor burdens of the mechanized MNM mining equipment used.

The project focused on identifying a suitable target (i.e., a mechanized mining machine) that would benefit from the application of automation technology. The project was limited to examining the problems with present mining methods and equipment.

Although the assessment process minimizes subjectivity, its intended use is as a tool to help in decision making. Decisions should also be based on a firm understanding of the subject matter and rational judgment. As such, in addition to collecting data and performing model development tasks, field visits to selected MNM mining companies were conducted to further the USBM's understanding of industry needs. The visits helped gain a company's perspective of the industry's direction and on mining automation, and helped validate the effectiveness of the model in identifying the needs.

MODELING THE ASSESSMENT PROCESS

A model of the assessment process, called the Minerals Mining Research Needs Analysis System (MMRNAS), was developed to provide an objective decision process for prioritizing the mining research needs of the MNM industry. MMRNAS addresses the following subjective factors:

- multiple commodities with varying ranges of importance,
- multiple and diverse mining methods,
- multiple issues causing problems-deficiencies (e.g., health, safety, and economic), and
- desire to get the greatest return for the research dollar.

The current version of MMRNAS can quantify health and safety deficiencies of MNM mining equipment and rank mining equipment based on those deficiencies. Further efforts on MMRNAS would enable it to match possible research solutions to deficiencies singled out in the first stage. It is the team's opinion that researchers and WO staff could use MMRNAS to better understand industry and its needs, to generate USBM research tasks, and to justify proposed USBM research.

DESCRIPTION

Computational Process

A mathematical method to compute the relative needs of mining equipment was developed. Its objective was to assess quantitatively the deficiencies of this equipment in terms of the health and safety of its operators who would be the direct beneficiaries of automation technology. The factors relevant to this objective are a count of each type of equipment and a quantitative evaluation of the severity of the health and safety hazards posed by each type. A further objective was to be able to emphasize the particular equipment used in mining a commodity that was "more valuable" to society (a commodity may be considered more valuable than another if the number of people employed to produce it or its annual economic dollar value is greater). Any given type of equipment engaged in mining a particular commodity at any given mine is burdened by a health severity rating that is equal to the following:

$$\sum_{cat} H_{cat} \cdot L \cdot C_{mine,\, commodity} \cdot R_{commodity},$$

where H_{cat} = deficiency rating for a particular health category,

L = labor force requirements for a type of equipment,

$C_{mine,\, commodity}$ = commodity production fraction,[5]

and $R_{commodity}$ = commodity rank (based upon annual tons, workers employed, or dollar value, normalized to 1).

Since any given mine can have more than one unit of equipment of the same type used in the same way, the overall mine health severity rating (HSR) of this equipment is

$$HSR_{mine,\, commodity} =$$

$$\sum_{cat} H_{cat} \cdot L \cdot U_{mine} \cdot C_{mine,\, commodity} \cdot R_{commodity},$$

where U_{mine} = number of units of equipment of the same type used in the same way.

Finally, the total, industry-wide health severity index (HSI) for a particular type of equipment can be represented as

$$HSI = \sum_{mine} \sum_{commodity} HSR_{mine,\, commodity} .$$

A safety severity index (SSI) could be developed using this methodology.

Equipment-Deficiency Input Data

To determine the severity of the effect of the equipment on the operator's personal well-being, data were collected that would allow for a quantitative evaluation of equipment deficiencies for each type of MNM mining equipment. Forty-six types of mechanized equipment used in MNM mining were identified and classified. From this list, only equipment that, taken together account for over 80% of equipment in use today, were selected for evaluation. Table 1 lists the 15 types of "high-usage" mining equipment.

A deficiency evaluation of the high-usage mining equipment was performed. Each type was evaluated against a set of health and safety criteria based on the subcategories of the Health and Safety Analysis Center (HSAC) data base. Each equipment deficiency received a "low," "medium," or "high" severity rating, with low suggesting little or no problem and high suggesting a severe problem.

An economic deficiency evaluation identified the current number of workers required for operation of each type of equipment and the projected reduction in labor (if any) when automated. Labor costs as a percentage of operation costs were determined. Operation costs as a percentage of total mining costs and equipment utilization and efficiency, before and after implementation of computer-assisted technology, were also determined.

Commodity Input Data

To determine the prevalence of the equipment's use in the industry as weighted by a commodity's importance would necessitate investigating all MNM mining equipment in use and the relative importance of all commodities. Because of the industry's scope, and USBM limitations in time and resources, it was necessary to limit the data-gathering process. Thus, data collection efforts were restricted to nine domestically mined commodities.

- copper (Cu)
- gold (Au)
- molybdenum (Mo)
- phosphate (Ph)
- platinum-group metals (PGMs)
- potash (Po)
- silver (Ag)
- sulfur (S)
- zinc (Zn)

The nine commodities, among the 33 minerals currently tracked by the USBM under its Minerals Availability Program (MAP), were selected because of their sensitivity to the U.S. economy.

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[5] If only one commodity is mined then C = 1. If multiple commodities are mined then C = annual production of a single commodity per total annual production of all commodities mined.

Table 1.—High-usage MNM mining equipment

Equipment description	ID	Mine cycle	Class
SURFACE			
Blasthole drill	BD	Fragmentation	Drill-blast.
Front-end loader	FEL	Materials handling	Loading.
Shovel	SH	. . do.	Do.
Truck	STK	. . do.	Hauling.
UNDERGROUND			
Boom-mounted face drill	FD	Fragmentation	Drill-blast.
Down-the-hole drill	DTH	. . do.	Do.
Gathering-arm-oscilоader	GAO	Materials handling	Loading.
Haulage load-haul-dump	HLHD	. . do.	Hauling.
Loading load-haul-dump	LLHD	. . do.	Loading.
Mobile-face conveyor	MFC	. . do.	Hauling.
Ring-longhole drill	RD	Fragmentation	Drill-blast.
Roadheader (continuous miner)	RH	. . do.	Mechanical.
Rock bolter	RB	Ground control	Drill-bolt.
Tunnel borer	TB	Fragmentation	Mechanical.
Truck	UTK	Materials handling	Hauling.

ID Identification.

Mine Input Data

Industry's scope and limited USBM resources again made it necessary to restrict the study to the top 100 domestic producing mines. The selected mines represent the top producers for each commodity, accounting for over 75 pct of domestic mine production. Using mine visits, personal contacts, published mining directories,[6,7] and the USBM's Minerals Availability System Data Base (MASDB), a set of data was collected identifying the commodity, mine name, deposit type, mining method, production, and ore grade for each mine.

A second set of data was also collected identifying the equipment and its prevalence at those mines where such data were available, leaving only 37 mines to consider in the evaluation since it was decided to consider only data from 1988 to the present. A 1988 cutoff ensured there would be no more than a 3-year difference between the equipment listings and associated production data. Otherwise, it would be inaccurate to match outdated mine equipment listings with recent production data (and vice versa). In searching the MASDB, full or partial equipment listings were found for only 25 of the 100 mines (1988 or later). Missing data and data on the 12 additional mines came from mine visits, published directories, and telephone contacts.

IMPLEMENTATION

The vast amount of mine, commodity, and equipment data was entered into seven data bases. A commercial relational data-base program was chosen as the software tool to perform the requisite task.

The seven data bases serve as the primary input to MMRNAS. They are described as follows:

- *Commodity Data Base*—contains information on employment, annual sales value, and production for each of the nine commodities.
- *Mine-Equipment Data Base*—contains a tabulation of the equipment used for each of the 100 mines. Since any one mine uses different types of equipment, there were several records for each mine, each listing a different type of equipment. There were a total of 530 mine-equipment records. Some of the equipment listed was not part of the high-usage equipment list and was not used in the model.
- *Mine-Production Data Base*—contains information on 100 mines assembled from the top producers for the nine commodities. Mines that produced byproducts were listed for each commodity (only if the byproduct was one of the nine commodities considered in the study), adding 15 records to the data base.
- *Health-Deficiency Data Base*—contains health-deficiency evaluation data on high-usage mining equipment.
- *Safety-Deficiency Data Base*—contains safety-deficiency evaluation data on the high-usage mining equipment.

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[6] E&MJ International Directory of Mining, Maclean Hunter Publications Co., 1991, 575 pp.

[7] Randall Mining Directory, Randall International LTD, 1990-1991, 482 pp.

- *Economic-Deficiency Data Base*—contains economic-deficiency evaluation data on the high-usage mining equipment.
- *High-Usage Equipment Data Base*—contains characteristic information on 15 types of high-usage mining equipment.

Figure 2 identifies the data fields in each primary input data base.

Ultimately, the model assigns a numerical value, or "severity index," to each type of high-usage mining equipment. To achieve this end MMRNAS begins by processing data found in primary input data bases. The result is an intermediate data base with fields consolidated (summed) or calculated from two or more of the input data-base fields. The next step is to process the intermediate data base with other data bases, intermediate or primary, to achieve a single output data base listing the equipment identification (ID) and associated severity index. Figure 3 shows this process.

There are 13 possible intermediate data bases and 2 possible output data bases; however, only 6 intermediate data bases and 1 output data base are created during one pass through the model. The seven data bases created depend on user input as described below. Each data base is the result of a computational step of the MMRNAS

MASTER EQUIPMENT DATA BASE

Equipment ID	Equipment description	Equipment class	Mine cycle	Mine operation

HIGH-USAGE EQUIPMENT DATA BASE

Equipment ID	Equipment description	Equipment class	Mine cycle	Mine operation

HEALTH-DEFICIENCY DATA BASE

Equipment ID	No. of miners affected	No. of lost days	Diesel particulate	Respirable dust	Nuisance dust	Blasting gases	Engine combustion	Chemical gases	Other gases	Continuous noise	Airblast noise	Heat stress	Psychological stress	Ergonomics

SAFETY-DEFICIENCY DATA BASE

Equipment ID	Total No. of mine accidents	Year	No. of accidents	Fatalities	Lost days	Ground control hazards	Fire and ignitions	Explosives and breaking agents	Struck by	Caught by	Power sources	Materials handling	Manual operations	Trips and falls

ECONOMIC-DEFICIENCY DATA BASE

Equipment ID	Operator labor before	Helper labor before	Operator labor after	Helper labor after	Type of operation	Labor operations	Operations total	Delays before	Delays after	Efficiency before	Efficiency after	Misc. No. 1	Misc. No. 2	Misc. No. 3	Misc. No. 4	Misc. No. 5

COMMODITY DATA BASE

Commodity	Descriptor	Employment (mine-mill)	Economic dollar value	Production (metric tons)

MINE-PRODUCTION DATA BASE

Sequence ID	Commodity	Deposit	Mining method	Production (short tons)	Grade (pct)

MINE-EQUIPMENT DATA BASE

Mine ID	Mining method	Equipment ID	Equipment description	No. of units

Figure 2.—Data field names for the contents of each primary input data base.

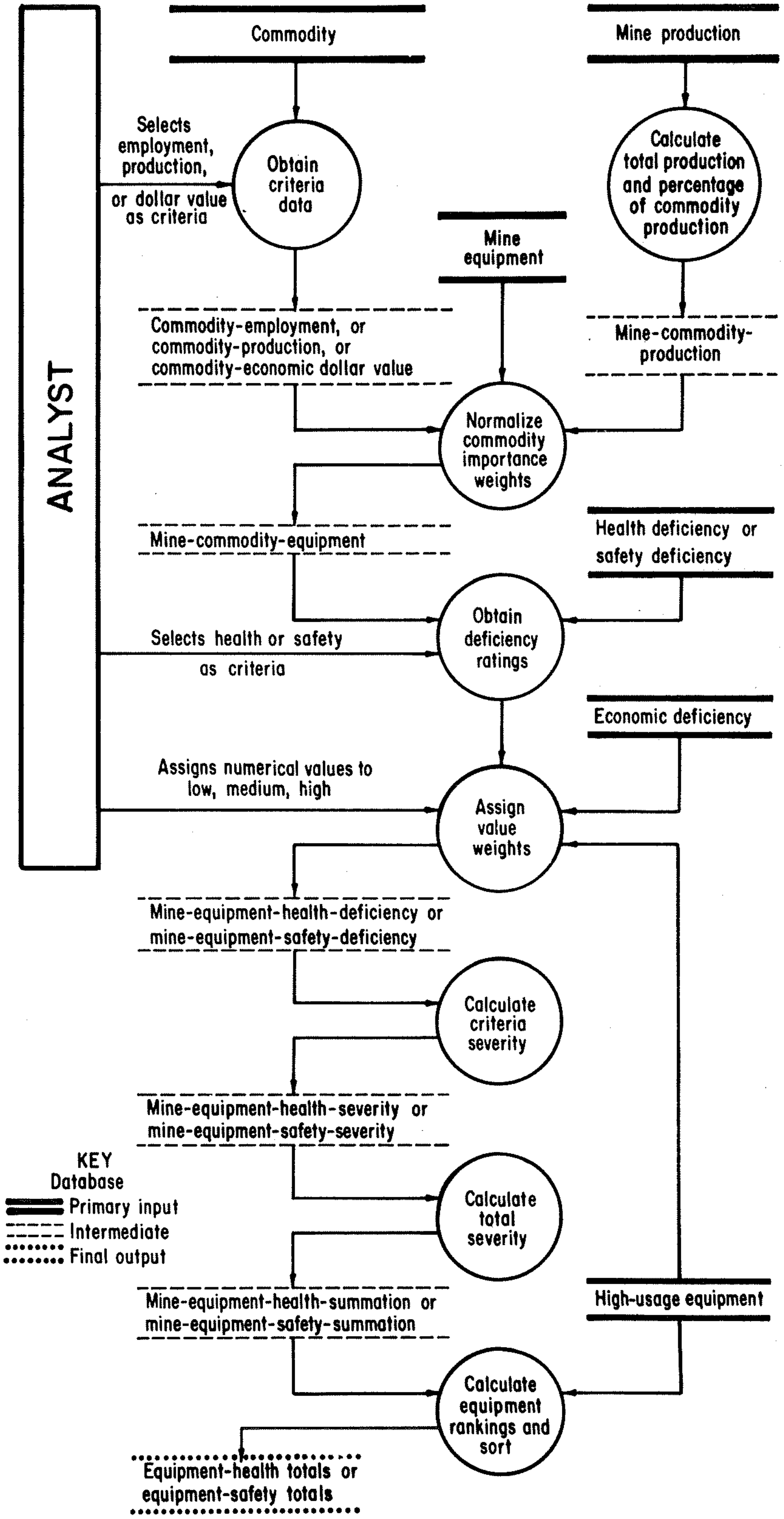

Figure 3.—Data flow diagram of MMRNAS.

model. Figure 4 shows the data fields in each of the intermediate and output data bases. The data bases and how they are created during one pass through the model are described as follows:

- *Commodity-Employment (or Economic Dollar Value or Economic-Dollar-Production) Data Base*—This data base is a subset of the primary *Commodity Data Base*. In building this data base the analyst must first select the criteria by which to weight the relative importance of the nine commodities. The options are number of persons employed, annual sales value, or production. The employment-weighted commodity data base is used in the example data bases below.

- *Mine-Commodity-Production Data Base*—This data base is derived from the primary *Mine-Production Data Base*. Because some mines listed in the primary data base produce more than one important commodity, the mine's equipment usage must be allocated among them in proportion to the amount of commodity produced. Thus, when this data base is created, the total commodity production and the fractional commodity production for each commodity mined is computed and recorded for all mines.

COMMODITY-EMPLOYMENT DATA BASE

Commodity	Descriptor	Employment (mine-mill)

COMMODITY-ECONOMIC DOLLAR VALUE DATA BASE

Commodity	Descriptor	Economic dollar value

COMMODITY-PRODUCTION DATA BASE

Commodity	Descriptor	Production (metric tons)

MINE-COMMODITY-PRODUCTION DATA BASE

Mine ID	Commodity	Deposit type	Mining method	Commodity production (short tons)	Mine production (short tons)	Commodity-mine production (pct)

MINE-COMMODITY-EQUIPMENT DATA BASE

Mine ID	Mining method	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity ranking

MINE-EQUIPMENT-HEALTH-DEFICIENCY DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Diesel particulate	Respirable dust	Nuisance dust	Blasting gases	Engine gases	Chemical gases	Other gases	Continuous noise	Airblast noise	Heat stress	Psychological stress	Ergonomics

MINE-EQUIPMENT-SAFETY-DEFICIENCY DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Ground control hazards	Fire and ignitions	Explosives and breaking agents	Struck by	Caught by	Power sources	Materials handling	Manual operation	Trips and falls

MINE-EQUIPMENT-HEALTH-SEVERITY DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Diesel particulate	Respirable dust	Nuisance dust	Blasting gases	Engine gases	Chemical gases	Other gases	Continuous noise	Airblast noise	Heat stress	Psychological stress	Ergonomics

MINE-EQUIPMENT-SAFETY-SEVERITY DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Ground control hazards	Fire and ignitions	Explosives and breaking agents	Struck by	Caught by	Power sources	Materials handling	Manual operation	Trips and falls

MINE-EQUIPMENT-HEALTH-SUMMATION DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Health severity

MINE-EQUIPMENT-SAFETY-SUMMATION DATA BASE

Mine ID	Equipment ID	Equipment description	No. of units	Commodity	Commodity-mine production (pct)	Normalized commodity rank	Labor force	Safety severity

EQUIPMENT-HEALTH TOTALS DATA BASE

Equipment ID	Equipment description	Equipment class	Mine cycle	Mine operation	Severity index

EQUIPMENT-SAFETY TOTALS DATA BASE

Equipment ID	Equipment description	Equipment class	Mine cycle	Mine operation	Severity index

Figure 4.—Data field names for the contents of each derived and final output data base.

- *Mine-Commodity-Equipment Data Base*—This is a combination of three data bases: the two intermediate data bases above using commodity as the relational field and the primary *Mine-Equipment Data Base* using equipment ID as the relational field. In this step, the commodity importance value (whether annual value, employment, or production) in each record is normalized by dividing it by the largest value from the nine commodities.
- *Mine-Equipment-Health-Deficiency (or Mine-Equipment-Safety-Deficiency) Data Base*—This is a combination of four data bases: the intermediate *Mine-Commodity-Equipment Data Base* and the three primary data bases, *High-Usage Equipment, Health-Deficiency (or Safety-Deficiency), and Economic-Deficiency Data Bases.* Equipment ID is the relational field used to combine these data bases. In building this data base the analyst must first select the major criteria on which to base equipment deficiency ratings. The options are health or safety. The analyst is then required to enter numerical values to be assigned to the low, medium, and high health-deficiency (or safety-deficiency) ratings. The intermediate data base is then built where only those records from the *Mine-Commodity-Equipment Data Base* containing data on high-usage equipment are selected, thus this data base contains 273 fewer records. Deficiency ratings for each type of equipment are assigned to the corresponding record entries. Additionally, the number of persons involved in the operation of each type of equipment (and thus exposed to the hazard) are taken from the *Economic-Deficiency Data Base* and recorded. The *Health-Deficiency Data Base* is used in the example data bases below.
- *Mine-Equipment-Health-Severity (orMineEquipment-Safety-Severity) Data Base*—This data base is the same as the intermediate data base above except that the numerical rating in each health (or safety) subcategory field is converted to weighted values. The value is a product of manpower, equipment usage, normalized commodity importance, fractional commodity production, and health (or safety) rating in each mine equipment record.
- *Mine-Equipment-Health-Summation (or Mine-Equipment-Safety-Summation) Data Base*—This data base is created by summing all 12 health (or 9 safety) fields of each equipment record in the data base above to form a single health-severity rating.
- *Equipment-Health-Totals (or Equipment-Health-Safety-Totals) Data Base*—This data base is created by summing the health (or safety) severity ratings for all equipment of the same type to yield a single severity-index value. This results in a data base containing one summary record for each of the 15 types of high-usage equipment that were found in use in 100 producing mines. Only 12 of the 15 types of equipment appeared in the end.

The Equipment-Health-Totals (or Equipment-Safety-Totals) Data Base is the final output data base and contains the desired result from the MMRNAS assessment process. When the equipment is sorted in descending order by the total-severity-index field, it represents a prioritized list of equipment in order of greatest need for research and greatest benefit to the mining industry using criteria deemed most important by the analyst.

RESULTS

The model gives an analyst the flexibility to experiment with numerous scenarios by selecting alternative commodity rankings and assigning alternative value weights to the deficiency criteria ratings. The committee tested several such scenarios to determine the system's sensitivity to these changes.

Figure 5 shows the results for eight different sets of analyst input. For each set of input, the analyst based the commodity importance on either annual value or employment, and the deficiency ratings on either health or safety. The analyst also assigned the low, medium, and high deficiency criteria ratings a value of 0, 1, and 2 or 0, 1, and 4. All eight combinations of user input were tested.

The number assigned to each bar of each bar graph indicates the equipment's degree of severity, 1 indicating most severe, or in terms of unit population, indicating the most prevalent. Unit population rankings did not come from MMRNAS, but were determined from a separate and distinct examination of the data-base data. The use of this information is discussed below.

Unit population and severity index rankings were normalized for scaling purposes.

DISCUSSION

The sensitivity tests allowed model developers to determine what effect a change in the set of input values had on the output results. In addition, it allowed them to determine whether or not unit population was an overriding factor in determining the outcome of equipment rank.

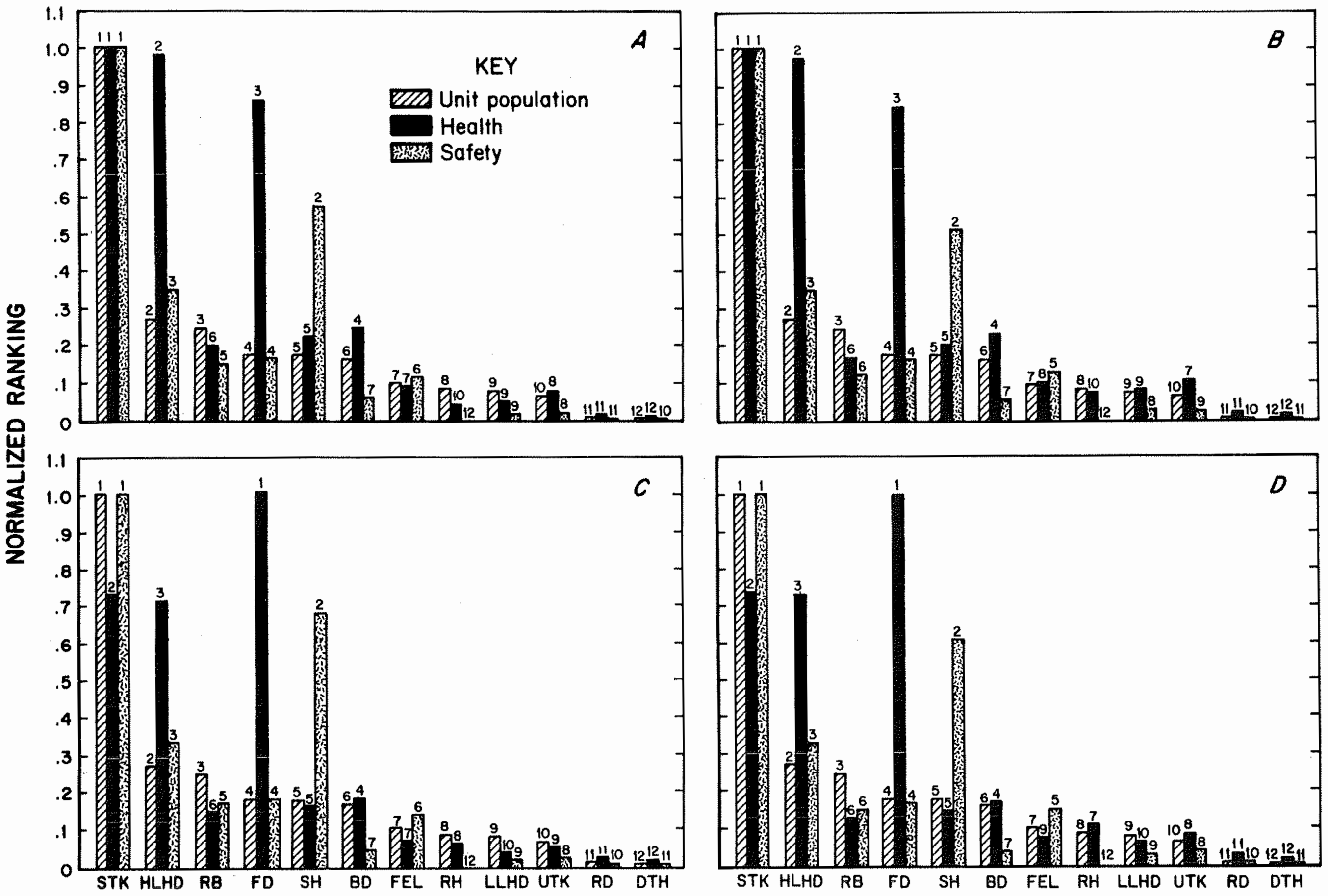

Figure 5.—Equipment rankings. *A*, Based on commodity-value and criteria-value weights 0, 1, 2; *B*, based on commodity-employment and criteria-value weights 0, 1, 2; *C*, based on commodity-value and criteria-value weights 0, 1, 4; *D*, based on commodity-employment and criteria-value weights 0, 1, 4. (See table 1 for definitions of abbreviations.)

The normalized rankings of figures 5 *A* through *D* are summarized in table 2. The data show equipment rankings for health and safety are not influenced by a change in commodity importance criteria, all other factors held constant. For example, results show health rankings based on low, medium, and high weights of 0, 1, and 2 are almost identical even though they are based on different commodity importance criteria. The model developers, however, expected a larger variation in the results. An examination of the commodity data base revealed that value and employment expressed as a percentage of total value and total employment are nearly the same for each of the nine commodities (fig. 6). It becomes obvious that employment levels are a relative gauge of commodity value and vice versa. Since MMRNAS uses normalized commodity importance weightings in computing equipment rankings, there will be little difference in the output results, again assuming all other factors held constant.

Table 2 shows surface trucks (STKs) and load-haul-dumps (LHDs) with a health severity ranking of 1 and 2. However, the relative difference between their scores as seen in figures 5 *A* and *B* is practically negligible despite the fact that MMRNAS considered four times as many STKs in its computation. Likewise, STKs and shovels (SHs) rank 1 and 2 in their safety index, even though SHs rank fifth in terms of unit population. This finding clearly indicates that unit population does not unduly influence the computational process and equipment rankings.

Table 2.—Equipment health and safety rankings based on differing weights given to deficiency criteria ratings and commodity importance.[1]

ID[2]	Unit Population	Criteria value weights based on low = 0, medium = 1, high = 2				Criteria value weights based on low = 0, medium = 1, high = 4			
		Value weighted[3]		Employment weighted[4]		Value weighted[3]		Employment weighted[4]	
		Health	Safety	Health	Safety	Health	Safety	Health	Safety
STK . . .	1	1	1	1	1	2	1	2	1
HLHD . .	2	2	3	2	3	3	3	3	3
RB	3	6	5	6	6	6	5	6	6
FD	4	3	4	3	4	1	4	1	4
SH	5	5	2	5	2	5	2	5	2
BD	6	4	7	4	7	4	7	4	7
FEL . . .	7	7	6	8	5	7	6	9	5
RH	8	10	12	10	12	8	12	7	12
LLHD . .	9	9	9	9	8	10	9	10	9
UTK . . .	10	8	8	7	9	9	8	8	8
RD	11	11	11	11	10	11	10	11	10
DTH . . .	12	12	10	12	11	12	11	12	11

ID Identification.

[1] Numbers 1 to 12 in the columns indicate the equipment's relative severity index ranking, "1" indicating most severe, or in terms of unit population, indicating the most prevalent.

[2] See table 1 for definitions of abbreviations under equipment description column.

[3] Commodity weight based on total annual value.

[4] Commodity weight based on employment levels.

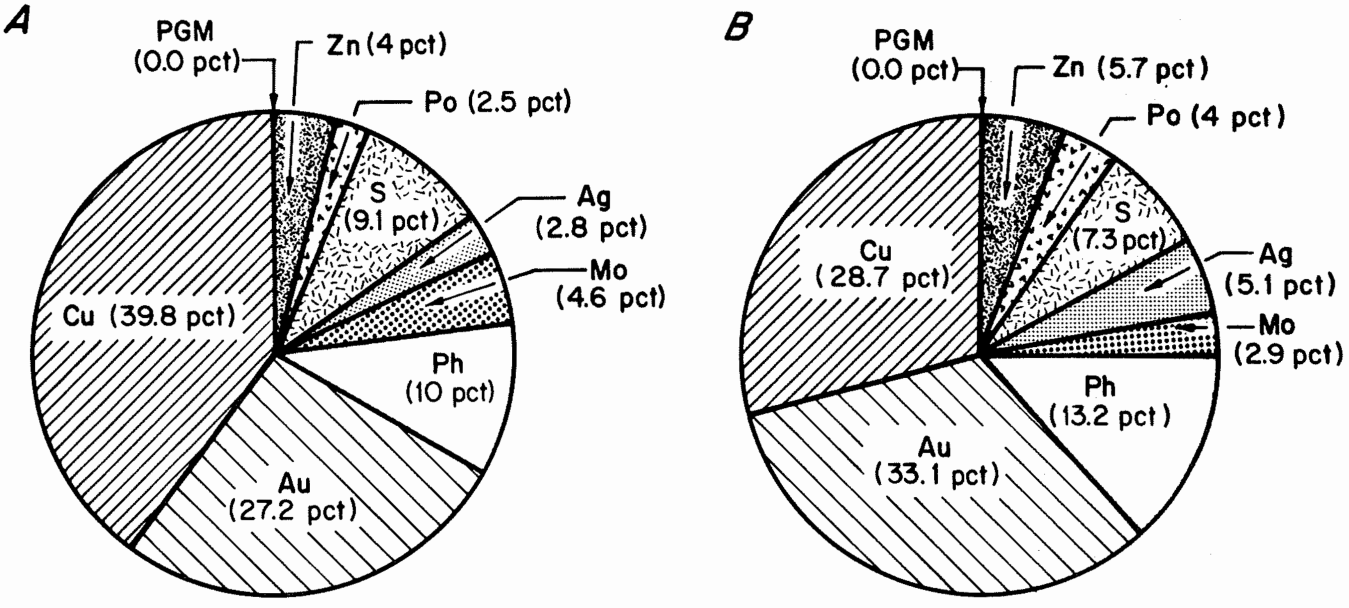

Figure 6.—Statistics for nine commodities. *A*, Expressed as percentage of total value; *B*, expressed as percentage of total employment. (PGMs = platinum-group metals; Ph = phosphate.)

Since there is a strong relationship between commodity value and employment, figures 5 *C* and *D* are also very similar. These two graphs mainly demonstrate MMRNAS's sensitivity to change in health and safety criteria values from 0, 1, and 2 to 0, 1, and 4, with high hazard being four times that of medium hazard rather than two times. Comparing the health severity rankings of figures 5 *C* and *D* to figures 5 *A* and *B*, face drills (FDs) rank number one, ahead of STKs and LHDs when high health carries four times more weight than medium. Previously, STKs and LHDs ranked 1 and 2. This suggests that FDs may have a greater number of serious health deficiencies than the other two types of equipment. Placing greater weight on the high rated deficiency criteria rating, places greater emphasis on equipment with serious deficiencies.

Comparing the safety severity ranking of both sets of graphs reveals little change in the equipment rankings. This indicates the majority of the safety deficiency criteria ratings were of low to medium importance.

MODELING AND DATA COLLECTION SHORTCOMINGS

Unrealistic expectations: Originally, the plan was to look at all mines and all data, creating generalities relating deposit types to mining methods, and production levels to equipment use and persons employed. Using current production data, the nature of the MNM mining industry when future deposits are mined would be predicted. It became obvious though that the data needed to support the original plan were not available in a common format, and location and methods to reach any conclusions were either too complex or the validity unprovable.

Little data on solid economic projections: The USBM team was reluctant to commit to speculative forecasting. The world's future is too uncertain to forecast mineral commodity needs. Thus, the study was limited to examining current mining methods and equipment, not potential revolutionary mining concepts like in situ mining, plasma blasting, or continuous fragmentation systems.

Inadequate reference base of mining equipment data: The main difficulty in collecting mine specific data was obtaining equipment lists for the 100 mines considered for this study. Original expectations included complete lists of mine equipment on a mine-by-mine basis, believing the MASDB contained the required information. The MASDB is a repository for mineral data collected by field personnel by direct questions or field surveys. Unfortunately, many data-base fields are empty. As a result, roughly 3 pct of the 3,000 plus mines in the MASDB have complete equipment information; in many cases the data are outdated. The lack of equipment data creates a very large gap in the USBM's awareness of industry's equipment usage.

Nonrepresentative data: Despite the successful completion of MMRNAS, the data used in the model do not represent a cross section of industry. For example, mine selection was limited to the top producers. Also, an initial examination of the raw equipment data revealed a lack of uniform equipment representation over the mining methods considered. Although statistically representative data were desired, data in general were hard to find. For the purpose of completing the model and demonstrating its usefulness, less concern was given to gathering statistically representative data and more concern was placed on simply getting data. However, to assess accurately and confidently industry needs, it is imperative that the data be representative of the industry as a whole.

INDUSTRY AND MANUFACTURER FIELD VISITS

The team sought the MNM industry's perspective on present and future mining needs and what automation research, if any, they were conducting. This input was important to appraise industry needs, validate model recommendations, and provide research program guidance. Team representatives contacted various mining groups to discuss these issues. Several subcommittees were formed to accomplish this task. One of these visited five groups, interviewing operating and engineering personnel both at the mines and at the corporate level. Based on these interviews, haulage equipment, especially trucks and LHDs, was the top choice for automation. The second choice was face-drilling equipment for underground operations. Both choices were prominent since they had high potential for improving productivity, health, and safety.

Another group of team members identified three broad areas for research: information systems, mechanical rock excavation, and automated materials handling. Industry recommended that information systems research be directed at better grade control, geologic hazard avoidance, and reports on operating equipment performance. Mechanical rock excavation research is important because the drill-blast-muck cycle constrains the operator's ability to improve productivity, and rock blasting causes rock mass structural damage, thus increasing the risk to underground personnel and reducing the available production time to make necessary repairs. Industry representatives believe that noncyclical mechanical rock excavation would be more systematic, more productive, and safer. In automated materials handling, industry representatives voiced the need for automated ore sorting, ore transportation, and ore processing equipment.

A third group met with industry and collected their own group of experts to make some suggestions based upon their knowledge of mining methods and equipment in the MNM mining industry. They found that the majority of underground accidents are associated with the fragmentation cycle, while the majority of surface accidents are associated with ore and waste haulage. The fragmentation cycle currently receives the most attention in underground mining automation research by industry and academia. Their research objective is to continuously mine in hardrock, because the conventional drill-blast-muck cycle hinders any substantial productivity increase. Present areas of research include applying impact hammers, compact tunnel boring machines, and integrated drill-load-shoot systems. Industry also expressed interest in researching sensor technology to distinguish ore from waste rock, an essential element in automated continuous hardrock mining, and supervised automation for repetitive tasks.

This group also found that surface mining equipment already performs at high productivity levels and, therefore, does not receive as much automation research attention as underground equipment. Most equipment research concentrates on automating blasthole drilling and developing guidance systems for haulage trucks, LHDs, and scooptrams. Industry, however, is hesitant to accept complete computer control of haulage trucks since it involves completely removing operators from the trucks. Mine operators suggested automating operation and monitoring of pumps and wells in the dewatering pits. However, the most prominent suggestion for research was diagnostic maintenance systems for surface equipment.

PRESENT AND FUTURE PROJECT DIRECTIONS

The MMRNAS results were quite successful; the model ranked some of the same highest priority areas of automation research in MNM mines as industry. But the real question facing the USBM still remains: "How can the Bureau use MMRNAS to evaluate and forecast all research needs?" To answer this question, one must take a much broader view of the mining industry and the mission of the USBM. Answers must indicate the status of the domestic mining industry and, maybe more importantly, where it is going. Answers must also reveal how the USBM's research should support that direction while supporting the needs of the taxpayer and the country as a whole. Finally, there must be a support structure to communicate these needs multilaterally, to the government structures [Office of Management and Budget (OMB) and Congress] that decide how to distribute funds among agencies, and to the researchers who apply and discover new technologies that support mining in this country.

Given the scope of this question, the original project focus of evaluating the automation needs of the MNM mining industry was updated. The focus is now on developing a traceable, hierarchical decision process to assist in developing research strategy, to provide guidance in developing research programs and project proposals, and to support the communication and justification of these programs, their objectives and priorities, to the USBM, Department of the Interior, OMB, and Congress.

To reach this goal, a new model must be developed using the data and some of the same techniques used to develop the initial MMRNAS model. The new model will extend beyond studying automation applications to studying all mining research program areas. One priority will be filling the holes in the existing data base, if possible. If the missing data cannot be found, the team will have to deal with the uncertainty element when offering advice on research strategies and deciding the programs to be developed.

Ideally, the existing MMRNAS data bases should also include information on present and long-term estimates of commodity supply and demand. In addition, there must be some provision for characterizing and classifying both known and unknown resources, and for estimating the potential for converting these resources into reserves. Finally, it is imperative that important criteria be identified that portray the USBM's mission and its research needs and strategies in order to support any advice given by this model. They must collect data from available resources to assess the criteria and support the model-generated results.

A new team of USBM researchers and managers from various research centers, WO staff engineers, and personnel from I&A was formed. This team brings together a broad spectrum of expertise in program and project generation and in MNM mining issues and information. The committee has met to discuss the criteria used for making program decisions and for designing the model using decision theory concepts. A strawman objective-value hierarchy has been developed that reflects USBM objectives concerning the environment, health and safety, national stability and security, and sound science, engineering, and economics in support of public policy. This hierarchy is being modeled using a decision-theory software package designed to allow an interactive decision-making tool. The new team is working individually on gathering additional data, as necessary, to support the analytical portion of the decision model. At each meeting the model is reviewed and necessary revisions are made.

For the model to be relevant, the data must be current, since the data input will change from year to year and decade to decade. For example, if the system includes data supporting an economic outlook of the mining industry, these data will change over time, very likely changing the resulting decision model output. Therefore, when the team has finished its work and a suitable model is available for USBM-wide use, the model will need continued maintenance to keep it up-to-date. A static data set offers no sound assistance in devising research program strategy very far into the future.

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