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Abstract

It is said that knowledge is power, yet often, decision makers ignore information that ought to be considered. The phenomenon known as Semmelweis reflex occurs when new knowledge is rejected because it contradicts established norms. The goal of evidence-based management (EBMgt) is to help overcome Semmelweis reflex by integrating evaluated external evidence with stakeholder preference, practitioner experiences, and context. This evaluated external evidence is the product of scientific research. In this paper, we demonstrate an EBMgt business analytics model that uses computer simulation to provide scientific evidence to help decision makers evaluate equipment replacement problems, specifically the parallel machine replacement problem. The business analytics application is demonstrated in the form of a fleet management problem for a state transportation agency. The resulting analysis uses real-world data allowing decision makers to unfreeze their current system, move to a new state, and re-freeze a new system.

Keywords

Evidence-based management, equipment replacement analysis, simulation

Disciplines

Business Administration, Management, and Operations | Business Analytics | Operations and Supply Chain Management | Strategic Management Policy | Technology and Innovation

Comments

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An Evidence-based Management Framework for Business Analytics

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It is said that knowledge is power, yet often, decision makers ignore information that ought to be considered. The phenomenon known as Semmelweis reflex occurs when new knowledge is rejected because it contradicts established norms. The goal of evidence-based management (EBMgt) is to help overcome Semmelweis reflex by integrating evaluated external evidence with stakeholder preference, practitioner experiences, and context. This evaluated external evidence is the product of scientific research. In this paper, we demonstrate an EBMgt business analytics model that uses computer simulation to provide scientific evidence to help decision makers evaluate equipment replacement problems, specifically the parallel machine replacement problem. The business analytics application is demonstrated in the form of a fleet management problem for a state transportation agency. The resulting analysis uses real-world data allowing decision makers to unfreeze their current system, move to a new state, and re-freeze a new system.

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Introduction

“In today’s increasingly dynamic environment, business schools must respond to the business world’s changing needs by providing relevant knowledge and skills to the communities they serve” (Association to Advance Collegiate Schools of Business (AACSB), 2018). This quote is found in the preamble of the AACSB business standards document focusing on engagement, innovation, and impact. Unfortunately, it seems that instead of drawing closer to industry, academia drifts farther away (Banks et al., 2016; Rynes & Bartunek, 2017). This academic-practice (A-P) gap has been noted and discussed in a multiple of disciplines over many decades. In business disciplines, one root cause of the gap is misaligned interests between academic researchers and practitioners. In other words, practitioners rarely find academic research interesting or helpful (McWilliams, Lockett, Katz, & Van Fleet, 2009; Schulz & Nicolai, 2015). In her 2005 Academy of Management Presidential Address, Denise Rousseau highlighted evidence-based management (EBMgt) as a way of translating research principles into organizational practice based on best available evidence (Rousseau, 2006). An EBMgt approach solves highly relevant business problems with appropriate methodologies and puts those recommendations into practice (Pfeffer & Sutton, 2006).

In the last two decades, EBMgt has grown in research prevalence. It has been put forward as a means of bridging the A-P gap, and while there has been over 100 articles specifically addressing EBMgt, nearly 80% of those articles have been either introduction and advocacy articles, essay and perspective pieces, teaching-related articles, reviews, or critiques and responses, leaving only 21% as empirical studies (Rynes & Bartunek, 2017). The general research problem we address is the A-P gap. Specifically, our research helps fill this gap by presenting an empirically-driven, business analytics research study using EBMgt as the framework to bridge the A-P gap. We describe the necessary EBMgt steps to successfully drive an empirical research project with a practitioner partner using business analytics techniques to derive actionable business findings that are also academically rigorous.

In their review of EBMgt literature, Rynes and Bartunek (2017) make five recommendations to researchers: 1) undertake more diverse systemic reviews, 2) study evidence of co-creation by academics and practitioners, 3) conduct studies of evidence use, 4) examine how well EBMgt actually works, and 5) mindfully ride the big data wave. The first recommendation is not the focus of this research, but the latter four are. In the context of business analytics, we describe how to co-create evidence in partnership with practitioners and how to demonstrate the use and efficacy of the evidence created.

An area of considerable interest among fleet managers and equipment maintenance managers has been determining the optimal level of equipment inventory and its maintenance (Hotelling, 1925; Taylor, 1923). Evaluating this tradeoff between inventory replenishment and maintenance has been a difficult challenge, especially when budgeting issues are a primary concern. Among a variety of organizations, equipment replacement analysis (ERA) has been a generally accepted approach for managing varying fleet sizes and types (Hartman & Tan, 2014). Now, with Industry 4.0 (Almada-Lobo, 2016; Battaïa, Otto, Sgarbossa, & Pesch, 2018; Lee, Kao, & Yang, 2014), organizations are capturing massive amounts of data from equipment and other sources, and they find themselves deluged with data while simultaneously lacking the capability to generate insights or improve their decisions. Managers are often left to rely on their own experiences, politics, incentives, and threats when making decisions (Rousseau, 2006). Fleet owners and operators need more than simple means and methods to take data and process them into actionable recommendations. Business analytic models and techniques present unique opportunities to bring practical yet innovative solutions and insights. Business analytic driven EBMgt will better help address problems as it considers different perspectives and matches “data” with intuition and experience.

In this research we combine business analytics with EBMgt and demonstrate how decision makers in general, and fleet managers in particular respond to problems within the context of their experiences, timeliness and relevance, the preferences of stakeholders, and the scientific external evidence. The scientific external evidence is grounded in ERA and implemented through computer simulation. We first discuss the origin and history of evidence-based practice and its more recent implementation in business management. This is followed by linking EBMgt to business analytics, detailing the importance of data, theory-driven models, and analytical methods. Next, following the six steps discussed in the EBMgt section, we present a real-world vehicle replacement problem (VRP) case using operational data. Next, the simulation model used to address the problem is described, followed by a discussion of the results. The analysis which results from using real-world data allows the decision makers to unfreeze their current system, move to a new state, and re-freeze a new system in a process similar to action research (Lewin, 1947). Finally, we provide general implications along with concluding remarks, limitations, and future work.

Evidence-based management

EBMgt is a data and theory-driven approach to decision-making, positing that while managers never have complete information in ever-changing environments, the quality of decisions is generally improved with the consideration of data-driven evidence (Pfeffer, 2010; Pfeffer & Sutton, 2006). It is "about making decisions through the conscientious, explicit, and judicious use of four sources of information: practitioner expertise and judgement, evidence from local context, a critical evaluation of the best available research evidence, and the perspectives of those people who might be affected by the decision" (Briner, Denyer, & Rousseau, 2009, p. 19) (See Figure 1). EBMgt has its roots in medicine, a field in which doctors must conscientiously, explicitly, and judiciously use "current best evidence" to make decisions regarding patient care (Pfeffer & Sutton, 2006). In EBMgt, principles are derived from research evidence and put into practice (Sackett, 1997; Sackett, Rosenberg, Gray, Haynes, & Richardson, 1996). One of the first recorded evidence-based medicine events was the discovery by Ignaz Semmelweis that doctors were causing infections and fatalities by not washing their hands between working on cadavers and seeing patients (Rousseau, 2006). Semmelweis became an early pioneer of antiseptic procedures even though it was strongly contested by his peers. Thus, Semmelweis reflex is now a term used to describe an automatic tendency to reject new evidence when it contradicts established norms.

[Figure 1 near here]

In the 1990s, evidence-based medicine gave birth to EBMgt in management research where using scientific knowledge informs the judgment of managers in organizational decision making (Briner et al., 2009; Rousseau, 2012; Sackett et al., 1996). EBMgt is a refinement in scholarly thinking of the relevance of research evidence in managerial decision processes (Wright et al., 2016). In evidence-based medicine, evaluated external evidence is often gathered through systematic reviews using the PICO approach:

P – Patient or problem. For whom is the evidence required?

I – Intervention. These are the effects of the activity being studied.

C – Comparison. What are the alternative interventions?

O – Outcomes. What are the effects of the intervention?

The classical definition of decision support systems (DSS) is a computer-based information system using data and/or models to help decision makers solve semi-structured or unstructured problems (Efraim, Jay, Liang, & McCarthy, 2001). Taking a problem (i.e., the P in PICO), applying a data-driven model to determine an outcome, and comparing (i.e., the C in PICO) that outcome with alternative interventions is the classical what-if analysis of DSS. This idea of data-driven decision making is an integral part of Holsapple, Lee-Post, and Pakath's business analytics framework (BAF) where evidence-based problem recognition and solutions happen in a business context (Holsapple, Lee-Post, & Pakath, 2014). Data-driven decisions are evidence-based, and organizations are moving into evidence-based analytics to gain a competitive advantage (Cho, Song, Comuzzi, & Yoo, 2017; Davenport, 2006; Wimmer, Yoon, & Sugumaran, 2016). Thus, DSS as a business analytics application belongs in the evaluated external evidence circle of EBMgt in Figure 1.

EBMgt is about making decisions through conscientious, explicit, and judicious use of the best available evidence from multiple sources to increase the chances of favourable outcomes. This is accomplished through the six A's:

1. *Asking:* translating a practical issue or problem into an answerable question.
2. *Acquiring:* systematically searching for and retrieving the evidence.
3. *Appraising:* critically judging the trustworthiness and relevance of the evidence.
4. *Aggregating:* weighing and pulling together the evidence.
5. *Applying:* incorporating the evidence into the decision-making process.
6. *Assessing:* evaluating the outcome of the decision taken (Barends, Rousseau, & Briner, 2014).

The intersection of EBMgt and analytics is particularly relevant to management science research but is often just mentioned in passing. For example, (Babai, Ali, & Nikolopoulos, 2012; Beynon, Curry, & Morgan, 2000; Danese, 2013; De Witte, Rogge, Cherchye, & Van Puyenbroeck, 2013; Ferreira & Marques, 2018; Hsu & Wang, 2013; Katsikopoulos, Durbach, & Stewart, 2018; Moons, Waeyenbergh, & Pintelon, 2019; Samadi, Nagi, Semenov, & Nikolaev, 2018; Wood, Wells, Rice, & Linkov, 2018) all mention evidence or evidentiary approaches, but generally only as a way to position an analytical approach to solving a complicated problem. We offer practitioners and researchers a framework in which analytic applications may be positioned. Additionally, this framework highlights through the four elements of EBMgt the importance of data, models, stakeholders, and context in the design and implementation of business analytics solutions.

Companies use analytics to compete through innovations in optimized business processes (Prahalad & Krishnan, 1998), and optimized business processes are enabled through predictive analytics (Waller & Fawcett, 2013). Maintaining a fleet of vehicles is a task fraught with uncertainties and ripe for the application of data science. Waller and Fawcett define data science in the context of supply chain management (SCM) as “the application of quantitative and qualitative methods from a variety of disciplines in combination with SCM theory to solve relevant SCM problems and predict outcomes, taking into account data quality and availability issues” (Waller & Fawcett, 2013). We believe this definition should be expanded through BAF (Holsapple et al., 2014) and Hahn and Packowski’s framework for analytics applications in a supply chain context (Hahn & Packowski, 2015). We next describe our suggested expansion.

DSS research has existed for nearly half a century, but recently there has been an upsurge in interest in DSS techniques, tools, and implementation under the guise of “big data” and “business analytics” (Holsapple et al., 2014). The concept of big data has gained attention in the last several years, and generally refers to the increasing volume of data being collected in real time from a variety of sources. Business analytics problems are often positioned into three general categories: descriptive, predictive, and prescriptive (Waller & Fawcett, 2013). Hahn and Packowski (2015) create a framework that assigns four use cases into the prescriptive, predictive, and descriptive analytical approaches. The framework assists in the classification of in-memory analytics in a supply chain context. We believe the framework is quite helpful but propose an amendment to it as shown in Figure 2. First, we remove the column “Formal IT Systems as it does not apply to this specific research. Second, while the framework places forecasting and simulation into the predict-and-act use case and classifies them as predictive analytic approaches, those use cases may also be classified as prescriptive analytics. Additionally, while prescriptive analytics are model-driven, the parameters for these models are increasingly derived from big data analytics. We also posit that the sense-and-respond use case includes diagnostic analytics, which falls between descriptive and predictive analytics. Thus, we suggest the mapping of use case to analytics approach is more continuous than discrete. As such, we remove boundaries in the analytics approach as well as the DSS concept and show, by the addition of the background arrows, the continuous nature of the categorization of analytics concepts. Regardless, the framework is helpful in understanding and classifying types of business analytics. Our research fits in the predict-and-act and plan-and-optimize use cases. This predictive to prescriptive type of problem solving fits well in the PICO structure of EBMgt as interventions may be explored through modelling and simulation, and the results or outcomes may be compared to identify the alternatives for given user preferences or other constraints.

[Figure 2 near here]

The case of the Iowa Department of Transportation

Developing fleet management performance measures are deemed important, but most DOTs are yet to develop well-crafted metrics of performance (Wyrick & Storhaug, 2003). DOTs purchase and operate large fleets of vehicles and are typically constrained by governmental regulations and budgets, making them ideal candidates for an EBMgt business analytics application. We demonstrate a business analytics application of EBMgt pertaining to the replacement policy for single-axle snowploughs in the state of Iowa. We implemented a simulation application using actual data and stakeholder perspectives collected from the Iowa Department of Transportation to overcome the Semmelweis effect on the current normal replacement policy for vehicles.

In 2015, the Iowa DOT budgeted approximately $10.1M for replacement of aging heavy equipment. Of that $10.1M, approximately 77% or $7.88M was dedicated for single-axle and tandem-axle snowplough class vehicles. These two classes represent the largest portion of the annual budget for vehicle replacement. As a result, decisions surrounding the replacement and maintenance of these vehicles are of significant importance to the state. It was believed that the current normal replacement policy employed by the DOT was sub-optimal, and a new policy would produce cost savings by reducing overall maintenance costs.

In 2014, the Iowa DOT had a total of 364 single-axle snowploughs in inventory. The purchase price for this type of vehicle was approximately $150,000. In Iowa, the current normal replacement policy is to use a straight line, 15-year depreciation; thus, the oldest 1/15 = 6.67% of vehicles are scheduled to be replaced each year. This 15-year replacement policy was changed from the previous 12-year policy in 2002. The motivation for the change was a budget shortfall, where one of the steps taken by the state to address the shortfall was to increase the normal replacement policy time window. This change realized short-term savings, but those managing the fleet believed that the larger 15-year time window would result in a greater total cost of ownership through higher operation and maintenance (O&M) costs on an aging fleet.

Asking: translating a practical issue or problem into an answerable question.

The Iowa DOT (the practitioners) and university researchers (the academics) met several times in the beginning stages to scope the problem and to define an answerable question. The resulting question was, given the historical vehicle data collected by the DOT and appropriate business analytic methods, what should the normal replacement time frame be for equipment owned by the DOT to minimize total costs? This step required multiple meetings with appropriate stakeholders to define expected outcomes. The practitioners wanted a working solution that could be used to justify budgetary changes and continued analysis of other equipment. The academics wanted access to data and freedom to analyse and report findings irrespective of the outcome. That is to say, the academics wanted the freedom to publish findings whether or not the results were viewed as favourable by the practitioners. Once terms were agreed upon and explicitly articulated, the research team moved to the next step.

Acquiring: systematically searching for and retrieving the evidence.

Evidence for this business analytics problem came from multiple sources, data provided by the practitioners, practitioner judgement (e.g. residual value of vehicles over multiple time frames), evaluated external evidence in the form of empirically verified models and techniques (e.g. ERA and simulation), context, and stakeholders' preferences.

Data

The Iowa DOT provided nine years of historical evidence (covering 2005 to 2013) including purchase dates and costs, all maintenance dates and costs, vehicle usage (in hours or miles), and actual and estimated residual values for all vehicles. The estimated residual values were derived from actual data and internal expert opinion.

Equipment replacement analysis

As equipment ages, O&M costs increase, while the residual value of the equipment decreases. Consequently, there is a point in the life of equipment where it is costlier to keep than to replace. Determining that exact replacement point has been the focus of academics and practitioners for nearly a century (Hotelling, 1925; Taylor, 1923). Many models have been created to recommend good replacement rules with various parameters (Hartman & Tan, 2014).

Reliability of systems and equipment is extremely important when risk tolerance for failure is very low. There is a large body of work focused on determining when equipment might fail (Hildreth & Dewitt, 2016; McCall, 1965), replacement decisions (Adkins & Paxson, 2017), the timing of upgrades (Mukherji, Rajagopalan, & Tanniru, 2006), types of equipment failures (Gutierrez, 2013), and how to avoid them (Moghaddam & Usher, 2011). Statistical and analytical methods have been the foundation of these types of equipment studies (Meeker & Escobar, 2014; Meeker & Hong, 2014). The challenge of determining the optimal length of time to keep equipment continues to interest researchers (Jin & Kite-Powell, 2000), whether it is based on pure economics and taxation (Adkins & Paxson, 2013b; Gemmill & Jensen, 1988; Suzuki & Pautsch, 2005) or life-cycle cost analysis (Gransberg & O′Connor, 2015). Moreover, researchers have applied numerous analytical techniques to address equipment replacement, such as stochastic methods (Adkins & Paxson, 2013b; W. Fan, Machemehl, Gemar, & Brown, 2014; McCall, 1965; Ohlmann & Bean, 2009), dynamic programming (W. Fan, Machemehl, & Gemar, 2012), heuristics, (Saleh, Rosati, Sharawi, Wahed, & Balestra, 2014; Suzuki & Pautsch, 2005) fuzzy sets (Chang, 2005), and simulation (Huh, Roundy, & Çakanyildirim, 2006; Sigal, Pritsker, & Solberg, 1979).

Equivalent annual cost

The equivalent annual cost (EAC) is the cost per year of owning equipment for the life of the equipment and is computed by annualizing the cash flow across the service life of the equipment (Hartman & Tan, 2014).

$$EAC(n) = \left(\frac{r(1+r)^n}{(1+r)^n-1}\right)\left(p - \frac{s_n}{(1+r)^n} + \sum_{i=1}^{n} \frac{o_i}{(1+r)^i}\right) \quad (1)$$

In equation (1), the service life of the equipment is *n* periods, the periodic interest rate is *r*, and the purchase price of the equipment is *p*. The residual or salvage value of a vehicle *n* periods old is s_n, and o_i is the operating and maintenance costs in period *i*. The value of *n* that minimizes the EAC of over the life of the equipment is its economic life (also known as life cycle cost (Eilon, King, & Hutchinson, 1966) or optimal life (Jin & Kite-Powell, 2000)) and is the optimal point for replacement. This general model serves as a foundation for evaluating the optimal point of replacing equipment under varying conditions but specifically focuses on serial equipment replacement.

Serial equipment replacement occurs when one machine is replaced by a similar machine at the end of its economic life (Brown, 1993; Vander Veen & Jordan, 1989). The serial replacement problem has been well-studied (Bean, Lohmann, & Smith, 1994; Fraser & Posey, 1989; Hopp & Nair, 1991). Other research has considered technological advances and the effect on replacement rules (Adkins & Paxson, 2013a; Bean et al., 1994). For example, newer equipment may be more efficient or have greater productivity and, thus, the replacement rule would be different than simply replacing like-for-like equipment.

Parallel machine replacement problem

An extension of ERA is the parallel machine replacement problem (PMRP). The PMRP finds the minimum cost replacement policy for a finite set of economically independent machines that operate in parallel. The PMRP generally takes the form of an asset currently owned (known as the defender) and one or more new assets considered to replace it (the challenger(s)). The PMRP has been used for fleet replacement models where economies of scale are a factor, multiple challengers exist from different vendors or newer technologies, budget constraints play a significant role in replacement choice, as well as other issues like government regulations, competition, and stakeholder preference (Keles & Hartman, 2004).

The majority of PMRP research has employed optimization and dynamic programing. These problems are computationally complex, generally requiring a simplification of the models for tractability. Historically, it has been necessary to make assumptions about O&M and other cost behaviours over the life of the equipment. A general assumption of O&M costs is that they are a non-decreasing function of asset age (Parthanadee, Buddhakulsomsiri, & Charnsethikul, 2012). This assumption has been well-studied in equipment replacement theory, but it assumes a constant utilization of equipment irrespective of age, which is not always the case. Older equipment may be used less due to the preference for newer equipment, resulting in O&M costs that are decreasing. Regardless of whether or not O&M costs are non-decreasing, as vehicles age the total cost of ownership increases as demonstrated in the cumulative cost model (CCM) introduced by Vorster (Vorster, 1980). The CCM is a graphical model depicting the increasing total cost of ownership for equipment as a function of age. We take a similar approach to CCM in evaluating the economic life of the equipment.

Because of the complexity of the PMRP, it has been necessary to simplify the problem space using rules such as no-splitting, where the optimal replacement policy ensures that equipment of the same age is either kept or replaced in their entirety. Another rule to simplify the solution space is the older cluster replacement rule where older equipment is replaced before newer equipment clusters irrespective of condition of the vehicle. Even with simplification rules, the PMRP is a difficult combinatorial problem (Jones, Zydiak, & Hopp, 1991). Consequently, a large portion of research in the PMRP demonstrates efficacy with smaller sample sizes to prevent computational overload. Thus, while the models demonstrate usefulness on smaller fleet sizes, when trying to apply them to larger fleets solution difficulty increases and often proves prohibitive. Moreover, many of the optimization models require deterministic parameters or application of a dynamic programming approach for stochastic variables (Childress & Durango ; Cohen, 2005)

Simulation

We have discussed a number of modelling techniques that can be used to assist decision makers facing the fleet management problem. However, many of these modelling techniques do not accommodate the inherent uncertainties in this problem, requiring them to be ignored, assumed away, or grossly oversimplified. Astute decision makers should view “optimal” solutions resulting from such models with a fair amount of scepticism because the solutions may be very sensitive to any deviations between the assumed values for model parameters and their ultimate realized values. In contrast, the technique of simulation exists specifically to deal with uncertainty in a very direct and explicit fashion (Kelton, 2016; Law & Kelton, 1991). As a result, simulation provides decision makers with information about the performance of various solutions in the presence of more realistic operating uncertainty. This allows decision makers to select solutions that are robust to the inherent uncertainties and more apt to deliver the desired level of performance when implemented in fleet replacement operations.

Among simulation techniques, the Monte Carlo method has been used to better understand equipment life-cycle analysis (Sigal et al., 1979). For example, in one study, Monte Carlo simulation revealed that the interest rate was a more important factor than the volatility of fuel prices, while engine efficiency was of the highest importance when considering optimal vehicle replacement (Gransberg & O′Connor, 2015). For an overview of the practices and research methodologies on equipment replacement optimization in commercial fleet management systems, see (H. Fan & Jin, 2011).

Appraising: critically judging the trustworthiness and relevance of the evidence.

Several data cleansing steps were taken to increase confidence in the data with the goal of eliminating errors while retaining valid outliers. First, only vehicles with an active status during the period of investigation were considered. Second, vehicles that were unmatched in inventory and maintenance records were flagged and either matched or discarded. Third, using outlier analysis, vehicles with possible errors such as excessively high maintenance costs or usage were flagged as suspect and further analysed for inclusion or deletion.

After the dataset had been extracted and cleansed, it was time-adjusted for simulation analysis. Following the general form of EAC, a periodic interest rate of 4.23% per year was derived from the actual data and applied to historical costs. Thus, the data for a vehicle that was one year old in 2005 were adjusted to be comparable to a one-year-old vehicle in 2013 in terms of labour rates and parts and vehicle costs. Vehicle usage is measured in hours of engine operation. Because the business analytics application considers both age and usage as variables for a new replacement policy, some descriptive analysis spanning the nine years of data provided is appropriate. One of the first analyses was to evaluate the average life usage of the vehicles in relation to their age. An example of this analysis is shown in Figure 3. For single-axle snowploughs across the state, the annual usage appeared to decrease as the vehicle aged. This is consistent with research showing user preference for newer vehicles (Parthanadee et al., 2012). Additionally, the Iowa DOT would occasionally keep vehicles beyond their economic life because they were perceived to be of additional value. These deviations from the current replacement policy exemplify the variability in human decision making, which often proves problematic for optimization methods. It also underscores the tremendous value of providing decision makers with the opportunity to evaluate various solutions while retaining control over the actual decision. This is consistent with the practitioner experience and judgment and stakeholder preference elements of EBMgt as shown in Figure 1.

[Figure 3 near here]

After the data were cleansed and the appropriate models were selected for the simulation analysis, they were reviewed and discussed by the academic-practitioner teams to ensure the trustworthiness of the selected evidence. One question presented by the researchers was the correlation between the age of vehicles and the maintenance costs. The researchers thought that it would be better to evaluate the vehicles based on their actual usage and not on age as it is possible that vehicles of the same age might be used differently, but the practitioners contended that they used their vehicles by age consistently across their fleet. A correlation analysis was performed on the age of the vehicles and their usage confirming the practitioners' assertions. The correlation between the age of the vehicles and the hourly usage was 0.918. Thus, the age of snowplough vehicles is trustworthy in the analysis of the replacement policy. Next, the evidence was combined into an evidence-based business analytics simulation.

Aggregating: weighing and pulling together the evidence.

Evidence-based business analytics simulation

We present an example of an evidence-based simulation application implemented in Microsoft Excel for the Iowa DOT's single-axel VRP. The choice of Excel was based on the availability of the platform within the DOT, the DOT personnel's relative comfort using spreadsheets, and the flexibility of the platform to generate the analysis for decision making (Ragsdale, 2014). This is vital because EBMgt tools for business analytics should be accessible to decision makers.

We are interested in determining a policy $\mathcal{P}$ for identifying the set of assets to replace in each time period j in order to minimize the expected annual operating cost defined as follows,

$$\underset{\mathcal{P}}{\text{MIN}}:\ \mathrm{E}\left[\sum_{j=\mathrm{N_T}+1}^{\mathrm{N}}\left(\sum_{i\in A_j} RC(\Omega_{ij}) + \sum_{i\in B_j} P_{ij} - \sum_{i\in S_j} RV(\Omega_{ij})\right)/(\mathrm{N}-\mathrm{N_T})\right] \tag{2}$$

Subject to:

$$A_{j+1} = A_j - S_j \cup B_j,\ \ \forall j \tag{3}$$

$$|B_j| = |S_j|, \forall j \tag{4}$$

where A_j is the set of assets in inventory at the start of time period j, S_j is the set of assets sold in time period j, B_j is the set of assets bought in time period j, P_{ij} equals the purchase cost of asset i in time period j, Ω_{ij} equals the age of asset i in time period j, $RC(\Omega_{ij})$ is the (random) repair cost associated with asset i at age Ω_{ij}, $RV(\Omega_{ij})$ is the (random) residual value associated with asset i at age Ω_{ij}, N is the number of periods in the planning horizon, and N_T is the number of periods in the transient state. Various policies $\mathcal{P}$ exist for identifying the set of assets S_j to replace in each time period. Because the Iowa DOT uses a time-based normal replacement policy, our application allows the user to evaluate alternative annual replacement policies based on vehicle age. Additionally, a cost-based replacement policy is also considered, as some vehicles of the same age might incur greater costs than others in the same time window. Historical data obtained from the DOT were used to generate the uncertainty distributions required for the simulation within the application.

Budgeting for governmental agencies like DOTs greatly complicates ERA, because budgets for vehicles must be established well in advance of the time of purchase. It would be ideal to allow organizations to monitor the condition of their fleet and replace vehicles as necessary, but currently, it is nearly impossible to generate a budget that would facilitate such a replacement policy. Thus, the Iowa DOT required an omnibus replacement policy.

Residual value of vehicles

The vehicles used in this study are valued based on their original purchase cost. An exponential depreciation curve was estimated based on historical data and practitioner experience and judgement from the left circle of Figure 1. This curve was validated by Iowa DOT internal experts, but the power of simulation analysis is its explicit handling of uncertainty and ease of adjusting parameters for future analysis. Thus, as new data becomes available, the residual value curve parameters may be updated to reflect actual sales. As shown in Figure 4, a vehicle loses its greatest value in the first few years and then levels off as the vehicle ages. In the present study, the residual values $RV(\Omega_{ij})$ for each vehicle i at age Ω_{ij} are modelled by a triangular distribution that requires a minimum, maximum, and most likely parameter estimates. A vehicle in the first year would lose at most 40%, at least 20% and most likely 30% of its original value. By allowing variability in the depreciation amounts each year, the simulation application can better account for the uncertainty in the final results.

[Figure 4 near here]

Repair cost distribution

To model the random maintenance costs, RC(Ω_{ij}), for vehicles as they age, we created a cost distribution based on historical data using cumulative time-adjusted maintenance costs for all single-axle snowplough vehicles in inventory between 2005 and 2013. We computed the minimum and maximum maintenance costs along with the 25th, 50th, and 75th percentile costs per vehicle in a given age and generated values for RC(Ω_{ij}), using the inverse transformation sampling technique. One drawback of this cost distribution's use is that in the data provided by the DOT, some vehicles were already in advanced age. For example, the minimum reported cumulative maintenance cost for vehicles 18 years old was $829, but that was due to not having the actual cumulative cost for the life of the vehicle as the data was a snapshot of nine years of maintenance. However, this was acceptable to the DOT as it drove the analysis toward a more conservative normal replacement policy (conservative from the perspective that the DOT believed state-level decision makers would prefer keeping vehicles longer rather than replacing them too quickly). This aspect of the simulation analysis could be strengthened by collecting a longer historical period of evidence.

This repair cost distribution for single-axle vehicles is shown graphically in Figure 5 in the form of a box and whisker plot for all vehicles of a specific age. Each year shows the quartiles along with the mean for the specific year and the cumulative mean calculated at that year. Note that at year 16, a decline begins in the specific year's mean but a continued increase in the cumulative mean occurs during that same year. It may also be observed that the upper whisker at year 18 has dropped to the same level as the cumulative mean. This drop is caused by vehicles with higher maintenance costs being removed from the fleet. Additionally, the length of the upper whisker begins to dramatically grow after year five indicating that some vehicles require costlier repairs in years six and later.

[Figure 5 near here]

Table 1 presents a summary of the variables used in this simulation, their definition, what is measured, and their source.

[Table 1 near here]

Simulation control parameters and process

The Iowa DOT's fleet management decision maker has several ways to control the simulation (see Figure 6 for a screenshot of the simulation user interface). The evidence-based simulation application allows the decision maker to evaluate replacing vehicles using a policy based on either vehicle age or cumulative maintenance cost. The user specifies the number of years to simulate, the number of years before the simulation reaches steady state, and the number of replications to run at each policy level.

[Figure 6 near here]

For example, using the settings shown in Figure 6, if the decision maker clicks the "Run by Age" button, for each possible trade age (i.e., 1, 2 … 16) the application simulates 300 years of operation, collecting data from years 51 to 300. The 300-year simulation at each trade age is replicated the specified number of times (30 times, in this case) and the results are summarized for each possible trade age. A similar process is followed if employing the "Run by Cost" policy, which involves replacing a specified number of vehicles each year (i.e., 20, 30, 40, 50 … 140), based on highest cumulative maintenance costs. Figure 7 summarizes the logic of the simulation process employed by the evidence-based simulation application. The simulation was implemented using

Excel's native Visual Basic for Applications (VBA) programming language (Alexander & Kusleika, 2016).

[Figure 7 near here]

Applying: incorporating the evidence into the decision-making process

The simulation application provides some interesting and useful insights for the single-axle snowplough. First is a confirmation of the tacit knowledge that the Iowa DOT was keeping these vehicles too long. However, based upon the initial results, the recommendation was an even shorter normal replacement policy than expected. Figure 8 illustrates that by moving from a 15-year to a 7-year replacement policy, the Iowa DOT could expect to save an average of approximately $1.88M annually. Additionally, while the average annual cost is minimized with a 7-year replacement policy, decision makers might prefer the 6-year replacement policy where a significant reduction in the standard deviation of the annual costs can be achieved by accepting a relatively small increase in expected annual costs relative to the 7-year policy. This provides another example of how EBMgt's explicit incorporation of practitioner judgment and preferences can led to better decision making.

[Figure 8 near here]

An astute decision maker should wonder to what extent the suggested 7-year replacement age policy in Figure 8 is sensitive to changes in the replacement price of the vehicle, the distribution of maintenance costs, and/or the assumed residual value curves. Figure 9 provides a sensitivity analysis of the factors showing how the recommended (least cost) vehicle replacement age varies as the vehicle price, repair costs, and residual values are varied plus and minus 10 percent from their original (base case) values. Intuitively, as vehicle price decreases, optimal replacement age also decreases (i.e., if vehicles are less expensive to buy, it is more economical to buy them more often). Conversely, as residual value decreases, optimal replacement age increases (i.e., a vehicle that is worth less is relatively more expensive to replace). We also observe that as repair costs decrease, optimal replacement age increases (i.e., if it is less costly to repair vehicles, it is preferable to keep them longer). Finally, the table summarizing the interactions of change in these parameters indicates that the optimal replacement age is more apt to increase than decrease.

[Figure 9 near here]

Similar results emerge when investigating the replacement policy where the *n* vehicles with the highest cumulative maintenance costs are replaced each year. Figure 10 shows those simulation results. It is evident that by replacing the 60 vehicles with the highest cumulative maintenance costs each year, the average annual cost for single-axle snowploughs would be approximately $11.8M. It should be noted that the optimal average maintenance cost using replacement age was $11.7M, and both had similar standard deviations; thus, the savings from the two recommended replacement policies are likely not significantly different from each other.

[Figure 10 near here]

Figure 11 provides a sensitivity analysis for the recommended number of vehicles to replace. Here again, we consider changes of plus or minus 10 percent from the original (base case) values of the replacement price of the vehicle, the distribution of maintenance costs, and/or the assumed residual value curves impact on the recommended number of vehicles to replace each year. These results show that as the vehicle price decreases, the optimal number to replace increases (i.e., if it is less expensive to buy new vehicles, more would be replaced). Additionally, as residual value decreases the optimal number to replace decreases (i.e., if owned vehicles are worth less it is relatively more expensive to replace them). Similarly, as repair costs decrease the optimal number to replace decreases (i.e., if repair costs are lower, vehicles would be repaired and kept longer). Here, the table summarizing the interactions of change in these parameters indicates that the optimal number to replace is more apt to decrease than increase.

[Figure 11 near here]

Assessing: evaluating the outcome of the decision taken.

The EBMgt business analytics application was used to evaluate the vehicle replacement policies of both single-axle and tandem-axle snowploughs. Tandem-axle results were not shown in this paper for space considerations, but the results were similar to single-axle replacement analysis. The initial results revealed that the current 15-year replacement policy was sub-optimal, but the Iowa DOT decision makers were surprised that a 7-year policy was recommended for the single-axle vehicle and a 6-year replacement policy for the tandem-axle. Since the majority of the fleet of snowploughs are currently past the recommended replacement age, the DOT needed to develop an action plan to take to state legislators. Consider how the four elements of EBMgt shown in Figure 1 inform this process. The experience and judgment of the DOT personnel was such that every divisional manager and maintenance manager knew that as the vehicles aged, repair costs exceeded its value. The drivers and mechanics preferred the newer vehicles for multiple reasons like reliability and state-of-the-art features. However, the budget to purchase new vehicles had to be approved by state legislators, and it was generally believed at that level that it was less expensive to repair older vehicles than to purchase new. Consequently, when the state budget was reduced in 2002, the choice was made to increase the normal replacement period for vehicles. When presented with the evaluated external evidence from the application, the DOT decision makers commented that it would be very difficult to convince legislators that substantial savings could be attained by increasing the budget for new vehicle purchases. This illustrates the importance of considering the intersection of all four elements of EBMgt. Organizations are often deluged in data, and there is an expected value in the data, but until a business analytics solution is applied using the evaluated external evidence, experience of experts, preference of stakeholders, and appropriately contextualized, sub-optimal decisions are likely to occur. It is unwise to ignore any of the EBMgt elements, and the best decision is one that values each. Therefore, a phased approach to modifying the normal replacement policy was recommended.

Simulation analyses (see Figure 8) indicate that single-axle (and tandem-axle) snowploughs appear to have a curvilinear relationship between age and replacement cost. Therefore, moving from a 15-year replacement policy to 12 or 13 years would still create savings to the state ($1.25M for single-axle snowploughs and $2.65M for tandem-axle snowploughs). While a two to three-year replacement window change would not yield the greatest savings, it would create savings over the current policy without incurring a massive budget change in the immediate year. It would also allow the DOT to improve the analysis with more evidence to verify the parameter estimates. In other words, it considers the legislative context (i.e. short-term budget constraints) as an appropriate influence in the decision. This three step approach is very similar to what Lewin proposed as a systems model for action research, unfreezing, moving to a new level, and re-freezing on the new level (Lewin, 1947). Consequently, the DOT was able to present the results of the analysis to state legislators, and they modified the normal replacement window from 15 years to 12. The DOT will continue to collect evidence to support their analyses and will revisit the budget discussion in the next two years.

Conclusions and future research

The goal of this research is to present a business analytics research project in an EBMgt framework that shows the co-creation of evidence in an A-P partnership, demonstrates how the evidence was used, how it performed, and how it influenced actual decision making. The context of the EBMgt solution approach is the fleet replacement problem. The six A's (asking, acquiring, appraising, aggregating, applying, and assessing) were used to frame the case of the Iowa DOT equipment replacement problem. The validated external evidence essential to EBMgt implemented through business analytics applications is ideally equipped to support the decision-making process. Two key components to effective analytics are data and data-driven models. Within the data-driven model approach, simulation lets decision makers allow for uncertainty in input parameters, providing a more realistic analysis of the data. We argue that our simulation approach provides analyses and recommendations that help to reduce Semmelweis reflex.

The approach presented in this research is an EBMgt analytics application adopting a PMRP model to allow decision makers to compare a defender against challengers at different replacement intervals. In the example of the single-axle snowplough VRP for the Iowa DOT, we aggregate all maintenance costs into an evidence-based simulation to determine when to replace vehicles in that class. Because of the highly variable nature of maintenance costs generated by different fleet owners and operators, we believe this approach to be generalizable in addressing ERA problems.

Like all model-based approaches, whether simulation or optimization, much depends upon assumptions. For example, the residual value curve is a critical component of the savings found in buying new vehicles versus continued upkeep of the existing fleet. Yet, the benefit of the simulation approach is the ability to modify the parameters as new data are available, or simply to compare “what-if” scenarios based on new parameters. Another limitation is the snapshot of the data creating the maintenance distribution. Fleet managers would be well-served to generate a new distribution from a wider window of data. Additionally, this particular application did not account for fuel consumption in total operating expense. The primary focus was on maintenance costs, but it is possible that fuel efficiency may be a factor influencing decision makers (i.e., challengers with technological improvements will affect the replacement policy). However, it is believed that for the next few generations of snowploughs, this is unlikely and consequently, was excluded from this analysis. PMRP research, as previously shown, can address challengers with technological advances. Lastly, by not focusing on individual vehicle maintenance events, we potentially lose the ability to identify specific problem vehicles or predict when particular vehicles may fail; but that level of detail would be very difficult to budget at a state level and would require significant organizational change. It was, therefore, beyond the scope of this research.

While different methods to explore the ERA problem are available, additional work could be carried out to examine why certain machines show significant deviations from the norm (e.g., outliers of maintenance costs). Predictive analytic methods focusing on time series analysis of maintenance events, as well as incorporating other unstructured data, may provide insight on causes of failure. These approaches would serve as new evidence co-creation in a separate EBMgt business analytics study.

Finally, business analytics researchers should continue to demonstrate the appropriateness and impact of their work in the scope of business decision making. If business analytics research is to be adopted and used by practitioners, it is important that stakeholders be involved in the research process. By doing so, the A-P gap can be bridged. It is also critical to publish the research in peer-reviewed, academic publications, and this requires researchers apply the same level of rigor to the applied research as they would to traditional research. This synthesis of research with business application should be clearly articulated, and EBMgt provides an ideal structure to do so.

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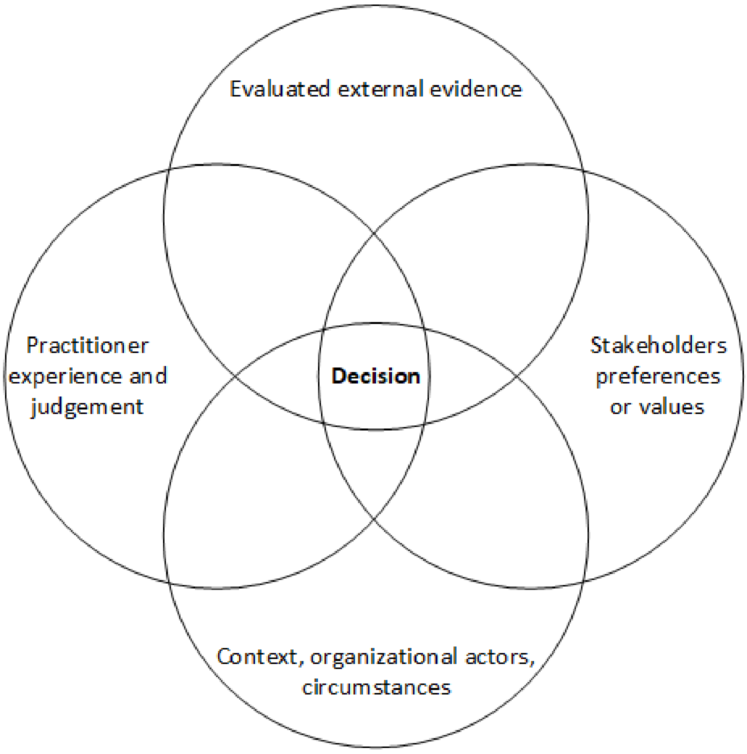


Figure 1. Four Elements of EBMgt.

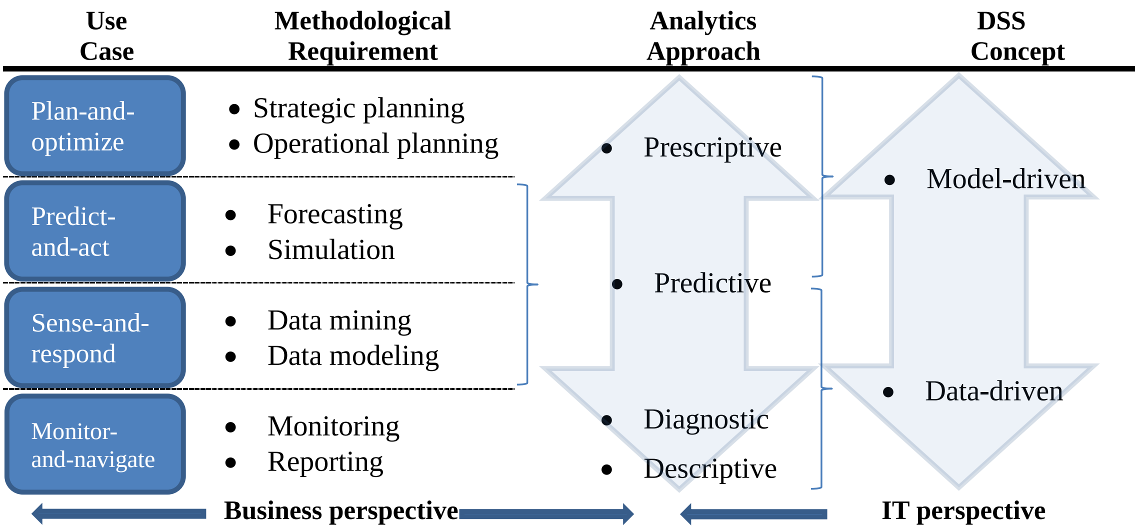


Figure 2. Adapted Hahn and Packowski (2015) analytical framework. Formal IT Systems has been removed, diagnostic analytics and arrows have been added to show the continuous rather than discreet nature of the analytics approach and DSS concept.

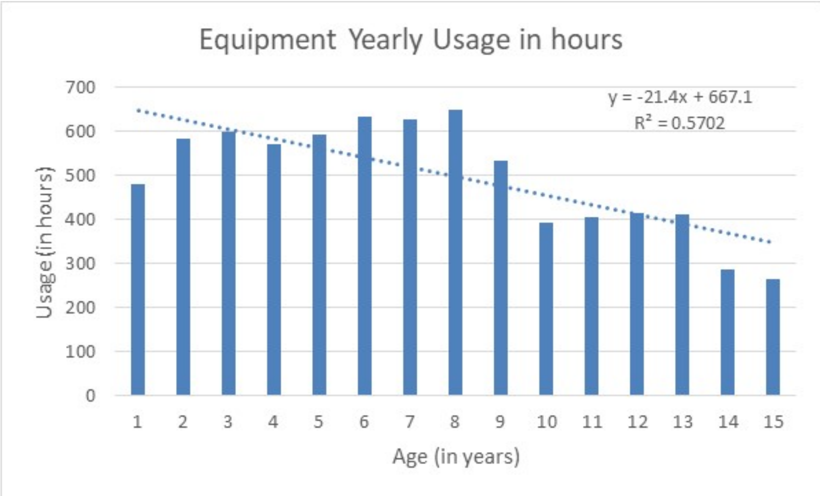


Figure 3. Average life usage of single-axle snowploughs by age.

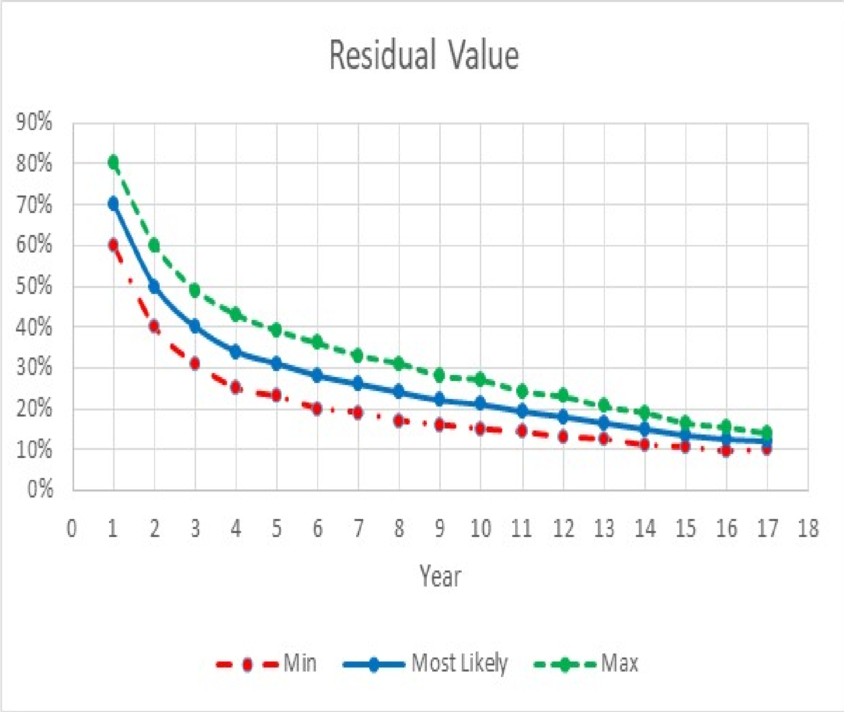


Figure 4. Exponentially depreciating residual value curve.

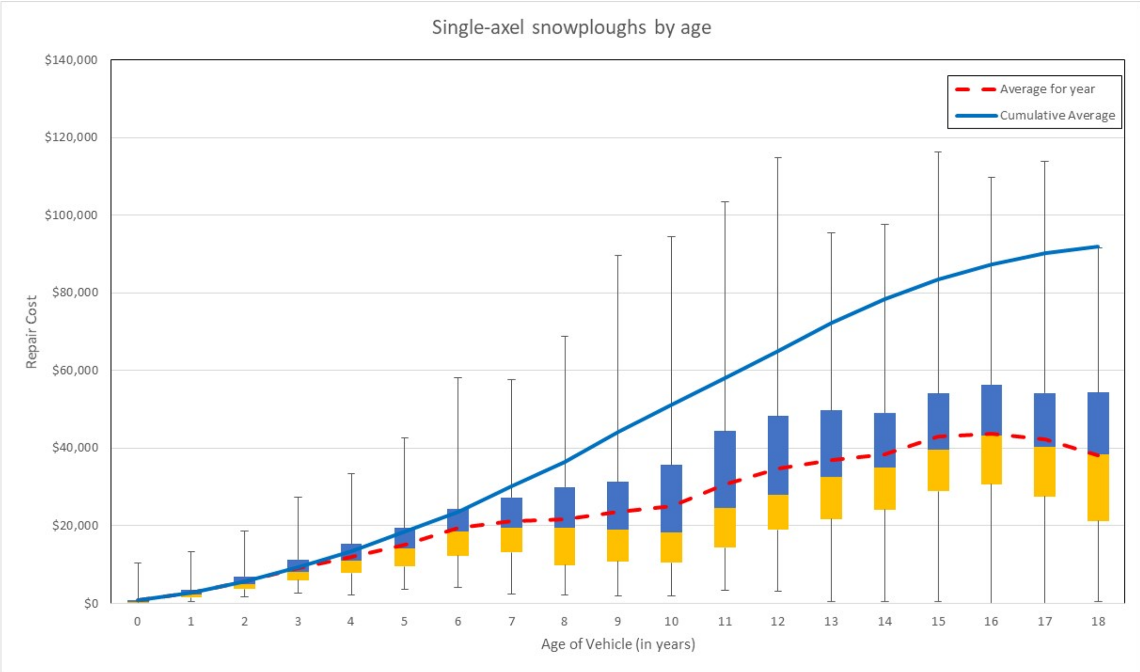


Figure 5. Repair cost of single-axle snowploughs by age.

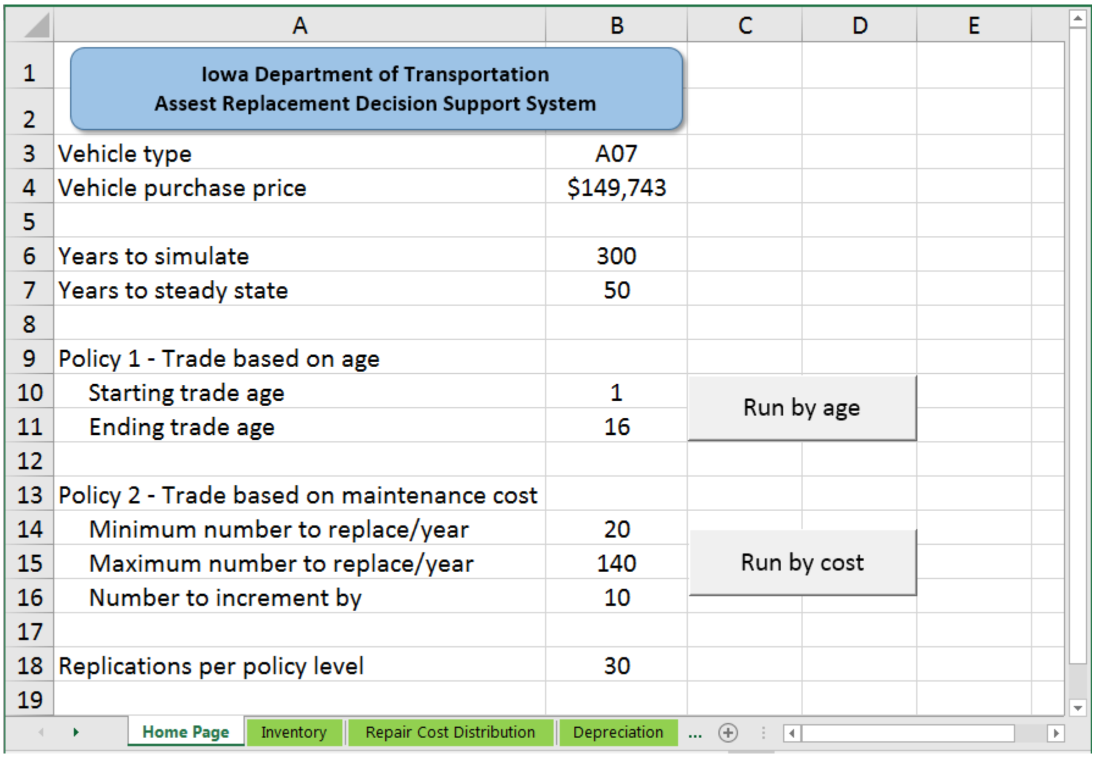


Figure 6. Simulation application interface.

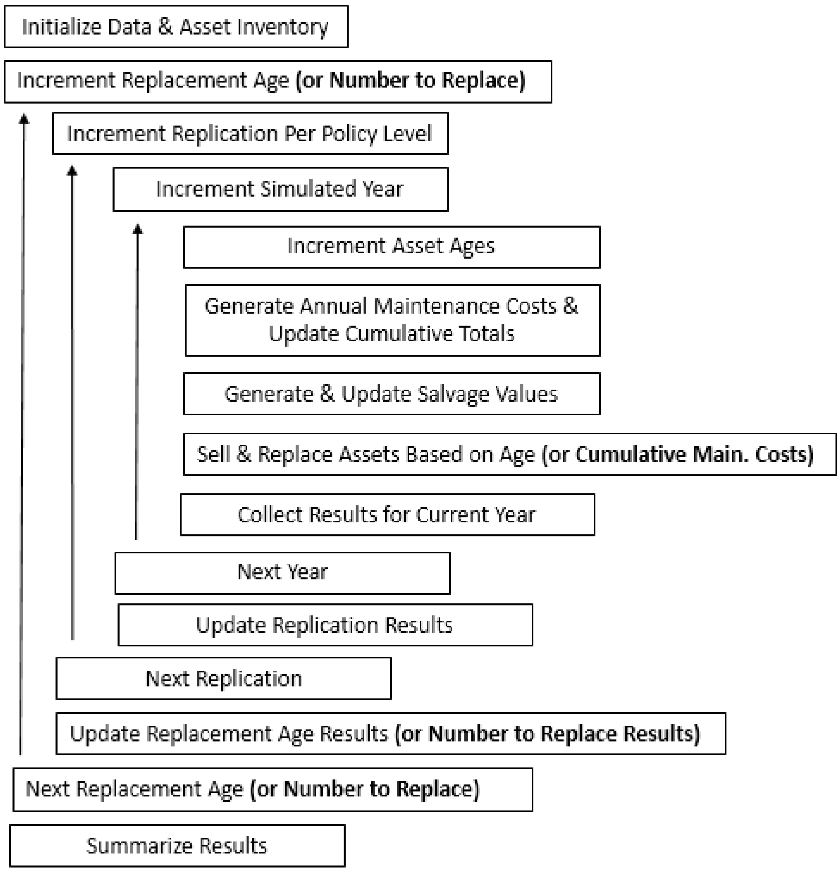
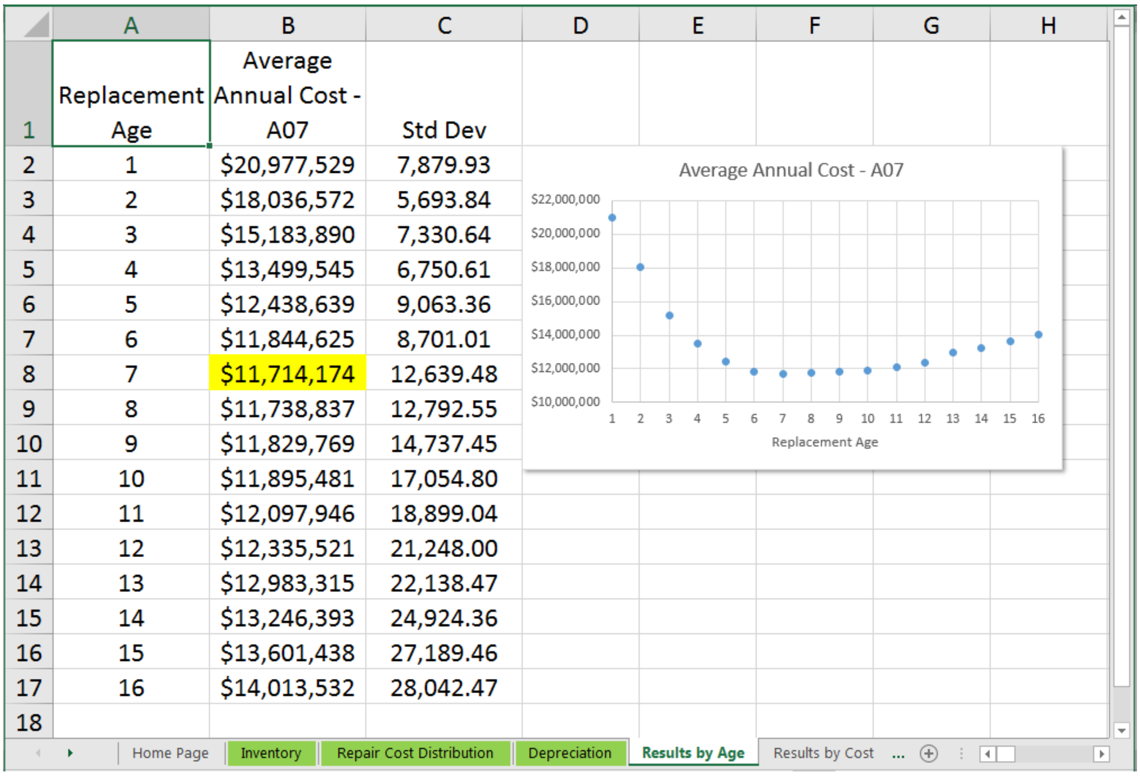


Figure 7. Summary of simulation process logic.



Replacement Age	Average Annual Cost - A07	Std Dev
1	$20,977,529	7,879.93
2	$18,036,572	5,693.84
3	$15,183,890	7,330.64
4	$13,499,545	6,750.61
5	$12,438,639	9,063.36
6	$11,844,625	8,701.01
7	$11,714,174	12,639.48
8	$11,738,837	12,792.55
9	$11,829,769	14,737.45
10	$11,895,481	17,054.80
11	$12,097,946	18,899.04
12	$12,335,521	21,248.00
13	$12,983,315	22,138.47
14	$13,246,393	24,924.36
15	$13,601,438	27,189.46
16	$14,013,532	28,042.47

Figure 8. Simulation results replacement policy based on vehicle age.

Salvage Value	Price	Repair Costs: High	Repair Costs: Base	Repair Costs: Low
High	High	7	7	10
High	Base	6	7	7
High	Low	6	6	7
Base	High	7	8	10
Base	Base	7	7	8
Base	Low	6	7	7
Low	High	8	10	10
Low	Base	7	8	10
Low	Low	7	7	8

Avg Replacement Age

	High	Base	Low
Price	8.56	7.44	6.78
Salvage Value	7.00	7.44	8.33
Repair Costs	6.78	7.44	8.56

Figure 9. Sensitivity analysis for replacement policy based on vehicle age.

Number to Replace	Average Annual Cost - A07	Std Dev
20	$15,933,331	31,944.41
30	$13,717,179	27,352.63
40	$12,313,398	20,206.29
50	$11,873,843	15,562.05
60	$11,819,124	10,897.33
70	$11,928,951	10,238.52
80	$12,173,512	9,085.91
90	$12,535,792	7,318.04
100	$12,961,305	7,481.08
110	$13,414,273	7,910.34
120	$13,868,598	7,460.22
130	$14,299,976	8,217.05
140	$14,651,177	8,986.84

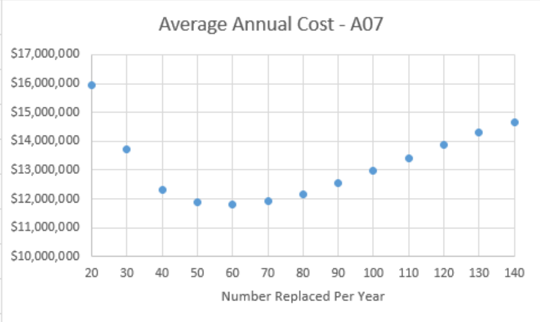


Figure 10. Simulation results for single-axle snowploughs based on maintenance costs.

Repair Costs

Salvage Value	Price	High	Base	Low
High	High	60	60	50
	Base	70	60	60
	Low	70	70	60
Base	High	60	50	50
	Base	60	60	50
	Low	70	60	60
Low	High	50	50	50
	Base	60	50	50
	Low	70	60	50

Avg Number to Replace

	High	Base	Low
Price	53.33	57.78	63.33
Salvage Value	62.22	57.78	54.44
Repair Costs	63.33	57.78	53.33

Figure 11. Sensitivity analysis for replacement policy based on maintenance costs.

	Definition	Measure	Source
Dependent variable			
Average annual cost	A measure of the total cost of ownership of a vehicle averaged by the number of years owned.	(purchase price + repair costs - residual value) / years owned	
Independent variable			
Purchase price	Historical price of vehicle purchased.	Actual cost of vehicle purchased	Data provided by Iowa DOT.
Residual value	The range of values a vehicle maintains given its age in years, adjusted for inflation.	An exponentially depreciating residual value curve with a min, max, and most likely value in any given year	Historical data provided by Iowa DOT and practitioner experience and judgement.
Repair cost	Cumulative, time-adjusted maintenance costs.	Average maintenance cost of vehicles in each year by min, 25th, 50th, 75th and Max percentile.	Data provided by Iowa DOT, normalized by inflation rates and split into quartiles.

Table 1. Variable definitions and sources.