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Buying for the Right Battle: Determining Defense Acquisition Strategies

October 27, 2020

Amirhossein Etemadi, Assistant Professor

The George Washington University

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Abstract

The Department of Defense (DoD) acquires operational systems via defense acquisition programs. It takes an average of about eight years to deliver a new system (or new capabilities) to the operating forces using existing acquisition processes. The duration between the start of system development until it is available for use is the program cycle time. Programs can execute as planned when program cycle times are shorter than the pace of technology and adversary change.

The pace of technology and adversary change is pushing the Department of Defense to streamline acquisition processes and deliver products faster. These process changes can deliver capabilities sooner, but with greater risk, effort, and cost. In extreme cases, Rapid Acquisition Offices are used to deliver interim solutions typically within two years of request. Such responsiveness requires extraordinary effort and leadership involvement to succeed. These rapid programs compete with existing programs for resources and priorities, meaning some still required programs will deliver required systems to the operating forces later and in smaller quantities than initially planned, unless changes are made to reduce their cycle times.

This research developed several research datasets from publicly available sources. Quantitative methods were used to identify significant cycle-time factors related to acquisition strategies, the defense market and program objectives. A decision framework is presented to help program management offices identify historical program precedents and potential acquisition strategy modifications to meet changing program cycle time objectives.

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Introduction

Former Secretary of Defense Mattis emphasized the need to deliver new capabilities at "*the speed of relevance"* (Mattis, 2018, p. 10). The Department of Defense (DoD) has accelerated certain projects, and focused priorities and resources to execute these projects. This research considers programs in the rest of the portfolio - those developing new capabilities that must accommodate changing priorities and resources and still deliver products – on time and as promised.

Programs can execute as planned when program cycle times are shorter than the pace of technology and adversary change. However, the pace of technology and adversary change is pushing the DoD to deliver some capabilities sooner[1], which often requires leadership involvement, greater risk, cost, effort and acquisition process modifications[2]. The result often is additional resources for accelerated programs, and other programs left with reduced budgets. A critical challenge is adapting their acquisition strategies to deliver required systems within the planned schedule.

Research scope

This research focused on selected Major Defense Acquisition Programs (MDAPs)[3] active between 2007 through 2018 within the context of a defense-unique market with multiple government stakeholders and increasing demand for reduced cycle time[4] and capability delivery. The market was defined by defense-unique commodities produced by the five largest defense contractors. Major policy changes[5] enacted between 2007 and 2018 provide context for the quantitative analysis of cycle time[6].

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[1] Rapid Acquisition Offices can deliver interim solutions within two years of request.
[2] Called streamlining or tailoring.
[3] MDAPs are weapon system programs with research and development expenditures greater than $300 million or procurement expenditures greater than $1.80 billion indexed to fiscal year 1990 constant dollars (10 USC 2430, 2007). The DoD also calls these Acquisition Category 1 (ACAT 1) programs.
[4] Cycle time is the duration between the start of system development until it is available for use.
[5] Specifically, the Weapons System Acquisition Reform Act of 2009 and the 2016 Section 804 Middle Tier of Acquisition.
[6] For example, the 2016 National Defense Authorization Section 804 changes requires capability delivery within five years of program start in order to use these authorities.

Research questions and objectives

The research investigated policy and management issues related to accelerating DoD acquisition processes, and is organized to answer the following questions:

1. *What data reported in publicly released reports are significant predictors of program cycle time and schedule change*? Cycle time is the duration between MDAP start and declaration of Initial Operational Capability (IOC) or equivalent. In this paper, cycle times are in months and program start means approval to commence engineering and manufacturing development (also called Milestone B). *Schedule change* is the relative percent change relative to original cycle time since program start.
2. *How do these predictors change with acquisition strategies*? Acquisition *strategies* are mandated by the Federal Acquisition Regulations (FAR) (General Services Administration, 2019a, pt. 7) , and include statements of capability needs or requirements, estimated development, procurement and sustainment costs, an integrated schedule, contracting and support plans, and procurement quantities. MDAP acquisition strategies include research and development activities when the objective capability is believed to require non-commercialized technologies (General Services Administration, 2019a, pt. 35).
3. *How does acquisition process streamlining affect these predictors*? Streamlining or tailoring in this paper means an approved deviation from an explicit requirement, standard, or practice with the intent to reduce program complexity, cost, or cycle time.
4. *What factors explain market condition effects on program cycle time*? Market conditions refers to factors affecting competition such as numbers of buyers and sellers, substitute goods, regulatory factors, and supply and demand[7].
5. *How do functional objectives change from program development through initial operational capability*? In this paper, *functional objective* means stakeholder objectives of cycle time, procurement quantities, or unit cost. MDAP capability requirements such as maximum speed are presumed unchanged. Programs proceed in sequential phases through program decision gates or milestones from program start[8] to initial operational capability (IOC).

This paper continues with a review of recent literature in Section 2. A methodology overview in Section 3 describes several databases developed from

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[7] Porter discussed these as market forces (Porter, 2008).

[8] This progression follows the Government Accountability Office (GAO) acquisition cycle knowledge points. Milestone B, approval to enter Engineering and Manufacturing Development (EMD) is knowledge point 1 (KP1); Critical Design Review (CDR) is KP2; and KP3 is Milestone C, approval for production and deployment (PD) (Dodaro, 2019, pp. 192–197). Most but not all MDAPs have these gates as part of their acquisition strategy.

publicly available sources and the quantitative methods used. Section 4 presents the results of quantitative analysis. Program cycle time and cycle time change models are provided to help program offices identify factors affecting cycle time reduction and growth from historical data. A decision framework is provided to help program offices and acquisition executives identify changes that have historically resulted in lower program cycle times with current constraints. Section 5 summarizes research results and suggests future opportunities.

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Literature Review

DoD acquisitions are part of a life-cycle process, with cradle-to-grave management assigned to a government activity such as a program office. This life cycle process extends beyond the service life of an individual system, as it includes pre-production activities and disposal (Kendall et al., 2015, p. 6). Acquisition programs typically include technology and system development in addition to procurement.

System schedule phases may be binned between development (which includes acquisition), procurement and operations and support (O&S). For example, the F-14 spent 6 years in development, was produced for 22 years, and was operational for 33 years (Anonymous, 2019c). The F-14 program overlapped development and production and additionally had concurrent production and operational service, resulting in about 17 percent of its service life spent in development, 61 percent in production, and 92 percent in operational service[9].

Platforms such as ships, aircraft, and vehicles are typically acquired using hardware-based production lines, which have finite production capacities. For example, the Joint Light Tactical Vehicle (JLTV) has a planned production buy of 58,306 vehicles (Dodaro, 2019, p. 89). Full rate production at current budget levels is about 2,500 vehicles per year (Anonymous, 2019b, pp. 45–54), meaning production to meet inventory requirements could continue for over 20 years.

Three interrelated processes control defense acquisitions: Requirements, Planning, Programming, Budgeting and Estimating, and Defense Acquisitions[10]. This research is focused on Defense Acquisitions. The literature review follows the research question sequence and presents cycle time-related predictor variables (2.1), acquisition

[9] These are relative to the service life.

[10] The Joint Requirements Oversight Council validates and approves new capability requirements, establishes cost (resource) and fielding (schedule) targets (McKenzie, 2018, p. A-1-A-2). The Department "facilitates the alignment of resources to prioritized capabilities" through the Planning, Programming, Budgeting and Execution process (Carter, 2017, p. 2). Defense Acquisitions are responsible for developing and procuring required capabilities within the provided resources (Kendall et al., 2015).

strategies (2.2), acquisition streamlining (2.3), the DoD market (2.4) and program functional objectives (2.5).

Cycle time predictors

Predictors from cost growth models

Cost growth is related to acquisition strategy factors such as prototyping, contract incentives in development and production, production competition, schedule concurrency and schedule slip (Arena et al., 2006, p. 13). Foreman identified longitudinal cost and schedule predictor variables based on SAR data. He showed that cost growth changes are related to procurement quantity changes, and depend weakly on schedule growth between production decision (Milestone C) and IOC (Foreman, 2007, pp. 65–77).

Sarmento and Renneboog analyzed cost growth (deviations) in Portuguese public infrastructure projects and found three statistically significant issues:

- having enough expertise to plan these types of projects,
- if the cost growth was to achieve political objectives[11], and
- having the experience to successfully execute such projects.(Sarmento & Renneboog, 2017, pp. 141–160).

Within the context of DoD MDAPs, these may translate to program office competence, influence from outside the program office, and contractor competence.

Better Buying Power was a process improvement initiative started by Gates in 2010 (Layden, 2012, p. vii) and expanded by Kendall in 2014 (Kendall, 2014a). This was policy and direction to “Buy more with no more” (Sanjay Sethi, 2015, p. 1). The initiative emphasized incentive-type contracts[12], affordability, cost savings and realism (Kendall, 2014a, p. 1). These have resulting in controlling unit cost, but are sensitive to schedule growth, quantity changes, cost definitions, inflation, and price adjustments. Three parameters important to Better Buying Power are procurement quantities, unit cost, and cycle times.

[11] Meaning cost growth increases if a contractor believes the government can be influenced.
[12] An indicator variable for use of incentive-type contracts was added to dataset observations.

Cost overruns can result in delays in development and procurement, resulting in schedule growth. Smirnoff and Hicks examined how externalities such as shrinkage of the defense contractor base, budgeting instabilities and statutory changes such as acquisition reform affect cost overruns (Smirnoff & Hicks, 2008, p. 3). Most of these externalities did not statistically effect acquisition cost performance. They offer an interesting speculation that when budgets are reduced, programs are not cancelled but "…continue on with inadequate funding that causes schedule delays and increased cost due to production breaks and orphaned technology…." (Smirnoff & Hicks, 2008, p. 11).

Tate et al. used Monte Carlo simulations to quantify program cost growth risks. They modelled historical development cost distributions as discrete and truncated Weibull distributions (Tate et al., 2018, p. 290). Significant predictors were the planned total development costs and number of development years funded, the distribution shape and scale parameters (indirectly aligns with commodity type), the service, budget "tightness" (funds availability and competition) and cost and schedule optimism (planned versus mean for commodity type) (Tate et al., 2018, p. 295). Externality measures include the competition reflected by budget tightness and cost and schedule optimism.

Program and schedule-related predictors

Light et al. developed four program attributes that may be influenced by acquisition policy and are measurable in reported data: 1) completion of Milestone A[13] review; 2) share of research and development (R&D) budget expended prior to Milestone B; 3) planned concurrency; and 4) joint or single-service program (Light et al., 2017, pp. 11–12). They found: 1) Completion of Milestone A review development reduced cost growth risk, but not unit cost growth risk; 2) more R&D expended prior to Milestone B reduced cost growth risk; 3) no measurable effect of concurrency on cost or schedule growth risk, and 4) Joint programs have more unit cost growth risk (Light et al., 2017, pp. 27–33).

[13] Milestone A is approval to enter technology development and risk reduction.

Holloman et al. used SAR summary variance data to create cost, time and technical system-level *degree of difficulty* indicators (Holloman et al., 2016, pp. 112–113) and GAO Annual Assessments of Selected Weapon Systems maturity assessment data to indicate *achieved* technical performance (Holloman et al., 2016, pp. 113–114). These enable program managers to characterize acquisition performance risk *during execution* from monitoring and control processes such as Earned Value Management (Holloman et al., 2016, pp. 111–112)[14].

Jimenez et al. conducted a literature review to find historical schedule growth predictors and identified statistically significant schedule-related predictors from MDAP Selected Acquisition Reports (Jimenez et al., 2016, p. 115). Two variables were positively correlated to schedule growth between program start (Milestone B) and a production decision (Milestone C): research and development funds at program start, and program start on or after 1985 (Jimenez et al., 2016, p. 119). Two additional variables were negatively correlated with growth between Milestones B and C: percent research and development funds at program start, and program being a modification of an existing program or system (Jimenez et al., 2016, pp. 119–120).

Project schedule models

Wauters and Vanhoucke applied K-nearest neighbor methods to forecast project schedule and control methods (Wauters & Vanhoucke, 2017, p. 1097). They learned that K-nearest neighbor methods work best for repetitive projects or those with accurate variability estimates (Wauters & Vanhoucke, 2017, p. 1107), and that earned value/earned schedule approaches are best for controlling projects with high uncertainty (Wauters & Vanhoucke, 2017, p. 1108). Random forest methods have been used to create predictive contractor performance models (Gill et al., 2019) and provide an efficient method to identify important variables for use in a regression model (Grömping, 2009)[15].

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[14] Earned value tools relate project cost and schedule at the work breakdown structure level. For a discussion of Earned Value Management, see Wei et al. (Wei et al., 2016).

[15] Specific implementations of rando forest models for cycle time analysis are in the methodology section (3).

Capili developed a system dynamics model of how factors such as contract types, schedule, requirements and policy issues[16] can affect the ability of the government to implement Agile software development (Capili, 2018, p. vi). Agile contracting fixes the number of requirements or *story points* to be completed during the period of performance. Adding requirements during the Agile process results in *trades and reductions of story points delivered to stay within schedule and cost constraints* (Capili, 2018, p. 6). Capili argues the government acquisition constraints eliminate the ability of Agile processes to adapt to program changes (Capili, 2018, p. 23)[17].

Acquisition Strategies

The DoD buys products, tangible and intangible items and services collectively described as a *capability*. Acquisition *strategies* are plans developed by program offices and approved by senior leadership to deliver this capability. Acquisition plans include statutory and regulatory documents explicitly describing the *contracting and competition*[18] approaches (General Services Administration, 2019a, pt. 7)[19]. Acquisition statutes and policy emphasize acquisition of commercial products or non-developmental items (General Services Administration, 2019a, pt. 7.102) and "competition" and "innovation" during system development (General Services Administration, 2019a, pt. 34). One description of competition in the Federal Acquisition Regulations (FAR) is

> "… when two or more contractors, acting independently, actively contend for … business in a manner that ensures that the Government will be offered the lowest cost or price alternative or best technical design meeting its minimum needs…." (General Services Administration, 2019a, pt. 34).

Acquisition statutes and policy emphasize acquisition of commercial products or non-developmental items (General Services Administration, 2019a, pt. 7.102). When

[16] As an example, information assurance may be at the same time a story point, a policy and contract requirement.
[17] Case studies provided qualitative evidence of the effects of government constraints.
[18] The Federal Acquisition Regulations emphasize full and open competition and fixed-price contracts (General Services Administration, 2019a, pt. 7.105)
[19] Specific statutory requirements vary depending upon the contracting strategy (Anonymous, 2019a, pt. 7.103) and may include additional detail such as market surveys, performance criteria, and plans and requirements for technology development and risk management, test and evaluation and security (Anonymous, 2019a, pts. 7.103-105).

the capability is believed to require non-commercialized (not a product) technologies, acquisition strategies will typically include a research and development phase, adding additional complexity and requirements to the overall strategy (General Services Administration, 2019a, pt. 35).

Innovation is not explicitly defined within the FAR. According to the Defense Innovation Board, "Technology by itself is not innovation; the unique application of technology is" (Anonymous, n.d.). Steinbock considers DoD innovation within the larger global competition, and notes a gradual decline in DoD innovation, reduced U.S. global competitiveness and the rise of *cost innovation* for "… affordable, almost-world-class…." systems (Steinbock, 2014, p. 373).

Research and development activities create intellectual property, and companies profit from and use this property. Defense innovation results in part from intellectual property commercialization (Kalanje, 2019, pp. 1–3). Borowski argues that the government should acquire sufficient data rights to encourage competition and innovation, and failing to secure sufficient rights from a developer may limit the base of capable suppliers (Borowski, 2016, p. 183).

Defense contractor acquisition strategies

Caldwell and Howard described military procurements in the United Kingdom (UK) as "markets of one" or as "virtual domestic monopolies" (Caldwell & Howard, 2014, p. 279)[20]. Intermittent defense procurements led to bundling procurement and support activities, providing long-term revenues to suppliers with an emergent "co-creation of value" resulting in increasing dependence on the supplier for integration and on the buyer for active program leadership (Caldwell & Howard, 2014). These conditions resulted in three strategic issues for the UK: coaxing incremental long-term innovation from a supply base used to radical innovation; setting a procurement scale that forces suppliers to bid; and ensuring capability transfer from buyers to suppliers (Caldwell & Howard, 2014, pp. 285–287).

[20] Meaning there may exist only one capable domestic supplier.

Having less competition with similar buyer and seller relationships has been historically profitable. in the U.S. defense-unique product market[21]. Zhong and Gribben argue that contractor profitability is reasonable relative to contractor risk assumption, degree of innovation and market share or influence (Zhong & Gribbin, 2009). A limited study by Blank identified strategies for mid-tier companies to establish a competitive position[22] (Blank, 2019). Finally, Brindley, Wood, and Mullen argued that government downward cost pressures are forcing contractors to develop better understanding of *realistic costs* to deliver a product and what cost can be bid that will win a competition and earn a profit (Brindley et al., 2017).

Acquisition Strategy Models

The DoD provides starting acquisition model baselines (Kendall et al., 2015). These represent six common structures, containing hardware and software development, production, and operation and significant program phases and milestones. Programs are encouraged to modify or tailor these models to the planned MDAP's "unique character" (Kendall et al., 2015, p. 8). The GAO found variations within these models, such as planning to declare initial operational capability before completing initial operational test and evaluation (Dodaro, 2019, p. 66).

An acquisition strategy defines if *production* and *performance* requirements are delivered in either in a *single-step* or *incrementally*. Selected Acquisition Reports (SARs)[23] provide insight as to whether acquisition strategies deliver production and performance requirements in a single step or incrementally, suggesting classification by production model (such as a production line or software replication), and requirements fulfillment (complete or incremental). Mortlock examined the difficulty of developing an evolutionary acquisition strategy[24] based upon historical assessed technical risk, approved requirements, and planned funding. Using data from an actual program history, he led participants through decisions that a program office would make during

[21] In the 1980s, major defense contractor profits as measured by returns on assets were found to be above industry means for other than accounting reasons (McGowan & Vendrzyk, 2002).

[22] He found such strategies need: insight on government acquisition objectives, influence on government procurement direction, and investment to create a competitive advantage (Blank, 2019, p. 241).

[23] A report to Congress required by law (10 USC 2432, 1991).

[24] An incremental development and production approach (NDAA, 2002).

program strategy development. His research showed that affordability concerns drive cost and schedule constraints, leaving *incremental development* as one of the few strategy approaches for managing risk during development (Mortlock, 2019).

Acquisition strategies support national policy goals. Georgiev classified defense acquisition strategies into those seeking technology innovation (active or offensive) or adapting strategies to the current environment (passive or defensive), and the intended technology position (leader, follower, or outsider). He also provided a hybrid of strategic and balanced scorecards as a method to improve management decisions and results (Georgiev, 2010).

Lorell et al. compared six MDAPs with extreme cost growth and four with low cost growth and identified five salient program characteristics[25]. They noted "…most of the extreme cost-growth programs' problems stemmed from a gross underestimation of the complexities and uncertainties …in designing, developing, integrating, and producing very challenging technological systems…." (Lorell et al., 2017, p. 69) While their findings are specific for cost growth, technical maturity and integration complexity were shown to be related to schedule growth (Kamp, 2019).

The six defined DoD acquisition models[26] may be used to classify acquisition strategies. As an example, the GAO recently asked 45 MDAP program offices to identify their acquisition model. Of these,

- 29 of 45 self-identified as Hardware Intensive (14) or Dominant (15),
- 3 of 45 were Software Intensive (1) or Dominant (2),
- 2 of 45 were accelerated acquisitions,
- 8 of 45 were tailored acquisition programs, and
- 3 self -described their acquisition model as either not applicable or unknown (Dodaro, 2019, pp. 64–66).

[25] These are "insufficient technology maturity and higher integration complexity than anticipated; unclear, unstable, or unrealistic requirements, unrealistic cost estimates, adoption of acquisition strategies and program structures that lacked adequate processes for managing risk through incrementalism or through provision of appropriate oversight and incentives for the prime contractor, (and) use of a combined MS B/C milestone (assuming) that little or no RDT&E is required…." (Lorell et al., 2017).

[26] These are: Hardware Intensive, Defense Unique Software Intensive, Incrementally Deployed Software Intensive, Accelerated Acquisition, Hybrid A (Hardware Dominant) and Hybrid B (Software Dominant) (Kendall et al., 2015)

Mills used linear discriminant analysis to explore relating acquisition strategies to program performance indicators (Mills, 2018, p. 1). NASA mission data was used in the analysis. The research attempted to relate cost and schedule margins for a given technical performance to an optimum acquisition strategy; uncertainty and risk were not included in the analysis (Mills, 2018). The research method developed groupings but was unable to create a method to determine an optimum acquisition program strategy (Mills, 2018, p. 34).

Acquisition strategies may include multiple acquisitions operating with varying degrees of coordination and interaction, such as unconstrained or complex systems (Stuckey et al., 2017). Stummer and Heidenberger described a three-phase approach to creating a project portfolio: starting with a manageable proposal pool; create a linear programming model with interdependent, logical, strategic, benefit and resource constraints, and searching this space until a portfolio satisfies the decision-maker's preferences (Stummer & Heidenberger, 2003, pp. 176–180). The advantage of this approach is the application of a rigorous and traceable method of creating a portfolio. The challenge is in the definition, parameterization, and quantification of the constraints as the breadth of the portfolio expands. In contrast, Davendralingam and DeLaurentis treated delivering a new military capability as a system-of-systems portfolio optimization problem. They used a mixed integer quadratic programming approach to optimize the system-of-system portfolio maximizing portfolio performance while minimizing development risk and cost (Davendralingam & DeLaurentis, 2015, pp. 271–279). Portfolio interdependencies, risks and uncertainties are captured in this modeling approach.

Program strategies should be developed with these factors in mind, and effectiveness is observed as a project proceeds. Rendon et al. identified system-of-system-related acquisition issues such as control and program office staffing (Rendon et al., 2012, p. 475) and how these issues translate into modifications to contracting and organizational structures (Rendon et al., 2012, pp. 477–479). Zafar et al. recently expanded this work, examining how geographically distributed teams coordinate software integration management and execution, resource and change management (Zafar et al., 2018, p. 22232).

Roberts et al.. identified 3 levels of observed acquisition program complexity: a complex stand-alone system, a complex platform and a system-of-systems (Roberts et al., 2016, p. 114). They showed that program cost overruns are statistically related to the system complexity, in part because current cost estimating methods and processes are "… are less suited for complex systems such as system-of-system and Platform programs…." (Roberts et al., 2016, p. 130).

Program management and acquisition streamlining

Much of the program management literature represents a collective experience of *realized risk.* For example, the National Research Council identified "six seeds of failure" – starting a program[27] with unstable or incomplete requirements, relying on immature technology, systems being designed to be more complex than needed, complexity arising from system-of-system interactions or dependencies, leadership inexperience, and relying on "large amounts of new software" as reasons for program failure (National Research Council (U.S.). Air Force Studies Board, 2008, p. 82). Jovel and Jain identified five system architectural attributes affecting system integration *complexity*: an open systems approach, functional and physical modularity, hardware and software commonality, and technology familiarity (Jovel & Jain, 2009, p. 53). These attributes represent qualitative subject matter expert assessments of common causes for poor program performance.

Browning defined project management as a process to reduce the "…value at risk to zero…." (Browning, 2014, p. 595). He advanced the concept of *monetizing the value of project performance-related factors.* Each factor was parameterized as a fraction of the total program profit (*dependent variable*) as a function of a performance-related factor (such as range) (Browning, 2014, p. 585). These factors were also weighted by a normalized stakeholder importance. Performance outcome risk distributions were modeled as triangular distributions and were developed from subject matter expert estimates (Browning, 2014, p. 587). The process enabled clear design and development trades in terms of value at risk.

[27] Program start is equivalent to Milestone B.

Meier inferred 3 factors causing program cost overruns and schedule delays: ineffective human resources (practices), too many stakeholders, and industry consolidation (Meier, 2010, p. 29). He provides only qualitative support of his arguments, the elements of each factor, and their linkage to cost and schedule outcomes.

The literature suggests that schedule growth results from including immature technologies into a MDAP, resulting in technology maturation controlling schedule growth. Manuel developed program simulations and showed that the likelihood of maintaining planned schedule is low given the serial nature of development and production schedules and proposed focusing MDAPs on integration in order to control schedule growth and executing technology development outside the MDAP (Manuel, 2019).

Platforms are sometimes acquired through rapid acquisition processes. The DoD has identified common acquisition models (Kendall et al., 2015) and encourages program offices to tailor these models to meet their needs. *Tailoring* and *streamlining* describe efforts to reduce or modify required processes and activities to achieve a functional objective such as reducing cycle time. There are multiple websites[28] providing case studies, contacts, and best practice recommendations.

The Mine Resistant Armored Personnel Carrier (MRAP) tailored acquisitions for rapid delivery[29] and went from recognizing the need for protection in 2005 to initial contract awards in 2006, and over 13,000 MRAPs were in-theater by 2009 (Sullivan, 2009). By 2016, the services were divesting MRAP inventory – for example, the Army reduced requirements to 8,222 in 2016 (Anonymous, 2019b, p. 165). Technology development and integration and transition into a long-term acquisition program for sustainment continues today (Anonymous, 2019b, p. 165).

Wong argues that the MRAP was *delayed* due to two institutional factors: validating the urgency of need and the struggle to acquire systems meeting a long-term

[28] See https://aida.mitre.org/accelerate/ and https://www.dau.edu/tools/t/DoD-Sole-Source-Streamlining-Toolbox as examples.

[29] the MRAP started with commercial prototypes in survival testing concurrent with indefinite delivery quantity contract awards.

need or reacting to an urgent threat (Wong, 2016, pp. 132–134). These factors are part of current DoD capability requirements approval processes (McKenzie, 2018).

In 2016, Congress established a "Middle Tier Acquisition" Authority providing substantive authorities to streamline acquisition programs with the objective of delivering new capabilities within five years from start (National Defense Authorization Act for Fiscal Yar 2016, 2015, sec. 804). These authorities are instantiated in processes between existing Accelerated and Urgent Capability Acquisition models (Kendall et al., 2015, p. 13,143). However, the Department required nearly 2 years to issue formal implementation guidance, and programs are in the early stages of execution.

DoD rapid acquisition strategies

DoD rapid acquisition strategies are defined by existing regulations and statutes[30]. These are generally characterized by limited scope and quantified objectives, senior leadership support and oversight, resource prioritization ahead of other programs, and extensive customization of existing processes to achieve program objectives. Tate postulated that only a few acquisition strategies are capable of rapid fielding, specifically *using already mature or developed systems*, *incremental development and production* of limited or narrow capability improvements, and modular upgrades (Tate, 2016, p. 12). Schoeni defined three types of government acquisition strategies: coercion, public-private partnerships, and Competition using Open System Architectures (Schoeni, 2018a, p. 88). Of these, Schoeni finds that competition will likely result in innovation (Schoeni, 2018a, p. 89).

Incremental upgrades[31] are production expressions of evolutionary acquisition strategies which are intended to delivery new capability as rapidly as possible (Sylvester & Ferrara, 2003, p. 5). By managing production and deployment configurations, incremental upgrades can be used to align production lots with deliveries of capabilities that mature between production versions (Mortlock, 2019, p. 46).

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[30] See aida.mitre.org for more information.
[31] Also referred to in the literature as block upgrades or release versions.

Graviss explored tailoring systems engineering processes for acquisition programs. Tailoring represents modifications for unique program requirements, and may take the form of process element reuse, discarding certain elements, modification of existing methods or pre-staged adaptations (tailoring) (Graviss et al., 2016, p. 277). He proposed a rules-based framework to guide tailoring (Graviss et al., 2016, p. 279), and notes four project attributes[32] applicable to all organizations: "…*Life-cycle Approach, Project Scope, Complexity and Precedence of the System, and Organizational/ Enterprise Policies and Infrastructure*…." (Graviss et al., 2016, p. 281).

Agile development processes are often presented as models for rapid acquisition and development. Syeda explored what critical success factors (CSFs) are most important to effectively apply Agile software development methodologies to systems engineering projects. Subject matter experts and practitioners were surveyed and Mann-Whitney testing was used to establish statistical significance related to project success. The statistically significant CSFs identified by Syeda were: commitment to Agile methods; change management; communication and collaboration; team environment and dynamics; project execution and oversight; and delivery strategy (Syeda, 2018). Syeda noted:

> "Unfortunately, many projects are in a gray area where it is difficult to determine if Agile methods are appropriate, to what extend should they be employed, and whether the Agile methods would contribute to a successful implementation. Nonetheless, projects may fail when their characteristics, development environment, and engineering methodologies applied are not aligned…." (Syeda, 2018, p. 2)

Institutional barriers and streamlining

Blair et al. provide examples from NASA systems development and fielding and argue that most problems[33] in aerospace systems are due to problems with technical integration or system engineering deficiencies and in failing to understand interactions (Blair et al., 2011, p. 32). However, they also show that institutional mandates such as

[32] Graviss calls these "tailoring considerations".
[33] The authors assert 80 percent of problems are due to integration or system engineering failure without substantiation.

minimizing risk to astronauts also limit what can be eliminated from an acquisition program and adds time and cost to the acquisition strategy.[34]

Conley argued that failing to address human capital risks results in cost and schedule growth and the inability to implement acquisition reforms (Conley, 2018, p. 5). He used multiple regressions to demonstrate a statistically significant relationship between human capital and program performance by considering the return on investment of a human capital decision implementing knowledge-based acquisition practices (Dodaro, 2007, pp. 11–13). Conley found no significant relationship between human capital risk and cost performance (Conley, 2018, pp. 55–56), but a *significant relationship between human capital risk and schedule performance* (Conley, 2018, pp. 60–61).

Farmer analyzed MDAP program office organizational structures and their relationship to program success. Structures were parameterized by programmatic and organizational factors (Farmer, 2018, p. 48), and were proximity clustered using Gowers Similarity Coefficient (Farmer, 2018, p. 52). The research considered program management office typology by system integrator responsibility, and identified factors and values for five systems integration organizational structures (SIOS) (Farmer, 2018, p. 65). The most frequently successful SIOS were when the government was the system integrator or responsibility was delegated to a system integrator (Farmer, 2018, pp. 157–158). Common attributes of successful programs (such as no cost or schedule breach) were used to identify successful and unsuccessful programs and relate these to SIOS (Farmer, 2018, pp. 153–159).

Eisa et al. analyzed commercial engineering project management processes showed change propagation is related to interface complexity and negatively related to designer experience (Eisa et al., 2018, p. 10). Engineering change propagation is one cause of programmatic scope growth, and these results support efforts to simplify

[34] They also provide several examples where designs were limited by physics or system engineering maturity (Blair et al., 2011, pp. 87–98), and required extensive systems engineering efforts to deliver the intended system performance.

interfaces and increase design experience to reduce the risk of schedule growth. These findings are broadly useful to DoD acquisition programs.

The DoD Market

A market may be considered as a system of social relationships, positions, rules and artifacts (products) that earns firms income (Fourcade, 2007, p. 1019). The DoD Acquisition process creates markets for goods, with the DoD being the main buyer and the defense contractors being the suppliers. Walter describes this as an imperfect market, where suppliers are insufficiently competitive and the government is unpredictable (Walter, 2019a, pp. 2–3).

Defense acquisitions are often described in terms of cost, performance, and schedule. Cantwell et al. created a dynamic model of defense acquisitions that represented acquisition work flows as a control system and used this model to illustrate how the complex interactions between changes in budgets, requirements (performance), production quantities, schedule and work completion interact and the results of responses by a program manager to recover from program cost growth, program schedule growth, or failing to meet program performance goals (Cantwell et al., 2013). The authors caution that "…every acquisition program is unique and must be evaluated in its unique context…." (Cantwell et al., 2013, p. 102)

Market Description

Depeyre and Dumez describe the DoD acquisition market as a *monopsony*[35] facing an *oligopoly*[36] (Depeyre & Dumez, 2008, p. 227). FitzGerald et al. describe the DoD acquisition market as consisting of four competition segments: "…military-unique systems with constrained competition, …military-unique-systems with viable competition,…military adapted technology, … (and) purely commercial technology (FitzGerald et al., 2016, p. 8). In this research, a market exists between the DoD and a seller identified by a product and service code (PSC) (General Services Administration, 2020) and include products and services within FitzGerald's competition segments.

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[35] A monopsony is a market with one buyer.

[36] An oligopoly is a market with few sellers, in this paper meaning the five largest defense contractors: Lockheed Martin, Boeing, Northrop Grumman, Raytheon, and General Dynamics.

These PSCs identify what is being acquired and repeated awards indicate the ability of the seller to produce the product or service.

Competition in the DoD acquisition market

Acquisition statutes and policy emphasize acquisition of commercial products or non-developmental items (General Services Administration, 2019a, pt. 7.102) when possible and "competition" and "innovation" during system development (General Services Administration, 2019a, pt. 34). The Federal Acquisition Regulations (FAR) define competition as "… when two or more contractors, acting independently, actively contend for … business in a manner that ensures that the Government will be offered the lowest cost or price[37] alternative or best technical design meeting its minimum needs"(General Services Administration, 2019a, pt. 34). This means market competition needs 1) at least two competent providers within the oligopoly, and 2) that the monopsonist must define needs and evaluate proposals[38] with cost (price) and content satisfying monopsonist-defined objectives.

Hensel noted competition was reduced by defense contractor base consolidation during the 1990s (Hensel, 2010, p. 187). Walter argued that the market was responding to unreliable and unpredictable government direction and procurements, which resulted in less competition, supplier concentration, and uneven production capability (Walter, 2019b, p. 3,17).

Kendall noted that competition can incentivize lower costs and stimulate innovation, quality and performance (Kendall, 2014b, p. 1). Walter pointed out that competition in a program typically occurs during the cost-estimating phase and there are no competitors for future acquisitions[39] to drive efficiency (Walter, 2019b, p. 8). Schoeni reviewed alternatives to competition such as coercion and partnerships

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[37] Cost is what is paid by the contractor to create a product. Price is what the customer pays for the product.
[38] Also called a *bid*, offered in response to a solicitation.
[39] This is a type of vendor lock-in.

(collaboration) (Schoeni, 2018b, p. 88), and argued for competition in order to avoid vendor lock and provide industry market incentives (Schoeni, 2018b, p. 85) [40].

The Defense and Aerospace sector has outperformed the S&P 500 indices for 2006-2018 (Lineburger & Hussein, 2018, p. 17). Future planned procurements are reported as sales backlogs in corporate financial filings (10-Ks). For example, Lockheed Martin's 2019 10K reports 2018 net sales of $45.005 billion USD and states a 2018 product sales backlog of $130.5 billion USD, of which 38% ($45.59 billion USD) will be realized as revenue in 2019, and 66% by 2020 (Cox, 2019, pp. 59–65). Such results suggest profitable corporations with near-term favorable market conditions[41].

Porter considered competition from a market perspective and found that "…industry structure drives competition and profitability…."(Porter, 2008, p. 83). Laguerre concluded that companies creating defense-unique products[42] must be economically and strategically protected (Laguerre, 2009, p. 304). He found *contestability*[43] and a government-controlled technology development and refresh process[44] create an effective proxy for competition in defense-unique markets (Laguerre, 2009, p. 317). However, the DoD is active in defense-unique product market for defense goods and services[45] and commercial goods and services[46] markets (Day, 2012, p. 10). Day argues that the government's power to dictate prices as the sole buyer in the DoD acquisition market is mitigated by requirements, the political environment, and the necessity to keep the supplier in business (Day, 2012, p. 5). This necessity creates a *sovereign price*[47] for the commodity.

Levenson found that competition with the intent to reduce costs was in general more costly than sole-source procurements due to incumbent cost advantages and

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[40] Contract types are specified in Selected Acquisition Reports (SARs) and through the Federal Procurement Data System (FPDS). These data sources identify attributes such as incentives and fixed-price. Full and open competition is presumptive. Indicator data for other than full and open competition is recorded in FPDS.
[41] Recent commercial strategies include development of a service market complementary to direct procurements. These "after-market" products include maintenance, training, and logistics, and represent future year profits
[42] Such as combat aircraft.
[43] Contestability is the ability to enter or leave a market.
[44] The Common Operating System is an example of such a process.
[45] Such as combat aircraft and technical services for aircraft maintenance.
[46] Such as food and commercial freight services.
[47] Introduced by Laguerre (Laguerre, 2009, p. 303).

pricing accuracy (Levenson, 2014, p. 435). Competition on the basis of innovation improved cost outcomes when competitors provided design or production innovations that lowered costs (Levenson, 2014, p. 436).

Guertin and Womble argued the DoD could reduce the impact of budget cuts and cost growth using "an open business model…and increasing competition." (Guertin & Womble, 2012, p. 76) The competition would occur in a market where the program office creates competition by dividing a procurement into units "…just large enough to be worth the time and effort to compete … yet small enough to be …loosely coupled." (Guertin & Womble, 2012, p. 80) This strategy needs government management of both the modular systems integration process and scaled market competition.

Innovation in the DoD acquisition market

The Organization for Economic Cooperation and Development (OECD) defines innovation as:

> "… a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)…." (OECD Publishing, 2019, p. 20)

The OECD identifies eight areas of innovation activity (OECD Publishing, 2019, p. 87). Of these, research and development are explicitly funded by the DoD. Research intensity[48] in the DoD acquisition market is driven by government investment, program budgets, and acquisition strategies. According to Steinbock, defense contractor research intensity declined between 1999 and 2012, as sales grew faster than research budgets (Steinbock, 2014, p. 371). Bresler analyzed DoD innovation activity contract awards between January 2011 and January 2018 to learn how effective these processes were in finding, maturing and applying innovations to DoD problems (Bresler, 2018, p. 110). She found that of over 1.29 million awards, over 80 percent were won by established DoD contractors (Bresler, 2018, p. 117), illustrating the competitive advantage of experience.

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[48] Research Intensity is Corporate R&D/Sales. This paper uses a modified definition - R&D/ (R&D + Procurement).

DoD contractors invest in supporting research activities and practices, including intellectual property rights to obtain a competitive advantage relative to peers. Guan and Chen modeled national innovation system production and commercialization efficiency using a two-step partial least squares regression (Guan & Chen, 2012, p. 105). The model suggests that national innovation requires downstream product *commercialization* (Guan & Chen, 2012, p. 112). The authors note that commercialization is an industry responsibility (Guan & Chen, 2012, p. 109). These insights are useful during early market analysis when estimating where to search for new technologies.

Risk and risk-sharing in the DoD acquisition market

Oudot identified four risk areas in French Defense procurements: *contractual* and *direct financial* risks, which are related to government performance[49], and *technological* and *industrial* risks, which are related to contractor capabilities and execution (Oudot, 2010, pp. 206–213).

The DoD uses contracts and agreements to allocate risk between the government and the contractor. Firm-Fixed-Price type contracts transfer all cost risk to the contractor, and are typically used during mature production (Grady, 2016, p. 8). Incentive-type contracts reward outcomes such as cost control by a pre-defined award or incentive schedule. Some unintended consequences of such incentives can include inflated target prices and higher cost uncertainty (Boukendour & Hughes, 2014, p. 281).

Technological and industrial risks are retired by government investments to create new technology and develop or sustain production capacity. Adler et al. studied risk share in 240 Air Force contracts awarded between 1970 to 1993 (Adler et al., 2016, p. 917). They found that pooling risk requires interdependence and alternative structures such as public-private partnerships and Other Transaction-type agreements[50] were created as alternative risk-sharing agreements.

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[49] These include sustaining and providing unique resources such as range facilities and the ability of the government to sustain financial support for a given MDAP.

[50] These are intended for research, prototype development, and production following prototyping.

Functional objectives

Acquisition strategies are generally not publicly available; elements are summarized in publicly available documentation such as Selected Acquisition Reports, annual reports and budget submissions. As previously shown, acquisition strategies are indicated by decisions such as single-step or evolutionary acquisition (Mortlock, 2019), technical maturity choices (Georgiev, 2010), competition (Arena,2006) and constraints on cost, schedule and performance (Capili,2018).

Program functional objectives – the cost, time to deliver, quantities delivered and system performance – are the planned outcomes or results of the acquisition strategy. Cantwell, Sarkani and Mazzuchi used a systems dynamics model to examine different cost-reducing strategy responses as measured by these objectives (Cantwell et al., 2012). In their model, all responses resulted in performance reduction and fewer delivered systems; three of four responses reduced total cost, and three of four achieved required schedule (Cantwell et al., 2012, p. 101). This research will use cycle time, procurement quantities, and unit cost as explicit program functional objectives.

Unit cost is reported as procurement unit cost[51] and program acquisition unit cost[52]. The National Defense Strategy shift back to a great power competition (Grieco, 2018, p. 2) has elicited hopes for increased DoD procurements (Knowles, 2018). An analysis of the 2020 Defense budget found procurement budgets relatively unchanged with personnel budgets growing faster than the force size, implying constraints on achieving Nation Defense Strategy objectives (Harrison & Daniels, 2020, p. 23), increasing the relative value to a program of reducing unit costs.

Procurement quantities are established during the capability requirements approval process within the DoD (Wicecarver, 2017), setting market expectations absent a change in need or inventory depletion. Tate et al. suggested procurement quantities are linearly related to unit costs during production and showed that a ramp-up-to-linear model approximates procurement budgets (Tate et al., 2018, p. 290).

[51] Procurement unit cost = procurement budget/number of end items produced (10 USC 2432). This is equivalent to the DoD term Average Procurement Unit Cost (APUC).

[52] Program acquisition procurement unit cost (PAUC) = (development + procurement + system-specific construction)/number of end items produced (10 USC 2432).

Procurement quantities are approximately the procurement budget divided by unit cost. Some acquisition reforms did reduce procurement cost overruns[53] while inflation and sustained armed conflict led to procurement cost overruns (Smirnoff & Hicks, 2008, pp. 11–13).

Summary and Issues

Acquisition strategies describe *how* the DoD plans to acquire products. These acquisitions occur in a limited market, with imposed mandates for innovation, competition and efficient stewardship and execution. The literature has several examples of quantitative acquisition research for defense and non-defense applications. While there are differences in constraints and objectives, there are common processes and researchers have developed useful quantitative models and insights into acquisition management.

Program schedule growth is related to risk retirement. As the DoD acquires more complex systems, effective schedule growth management strategies include approaches to reduce development, integration and production complexity. The literature describes program characteristics related to cost and schedule growth. These relate to factors such as requirements and resource stability and understanding of the risks related to delivering products satisfying requirements within financial constraints and delivery schedule objectives.

Government and contractor programmatic plans include development, procurement, testing and sustainment. The literature identifies schedule growth predictors related to the initial capability descriptions, the available resources and delivery schedule, and the program risk elements affecting program schedule. These predictors may be outside program office control, and may change during program execution.

The next two sections of this report will focus on explaining how acquisition strategy cycle time functional objectives are affected by programmatic resource

[53] Specifically the Nunn–McCurdy Act of 1982, the Packard Commission Recommendations of 1986 and the Federal Acquisition Streamlining Act (FASA) of 1994 (Smirnoff & Hicks, 2008, p. 9)

allocations and strategy decisions both in planning and in execution. Two research hypotheses will be tested:

- Program cycle time may be predicted from programmatic resources and acquisition strategy decisions (H1), and
- Percent change in program cycle time may be predicted from programmatic structural changes (H2).

Methodology

This section reviews the research data collected, summarizes the response and predictor variables, explains the supporting quantitative methods used in the research.

Research design overview

The research datasets were created from publicly available sources. Statistical analyses were conducted using Minitab18, SPSS, and selected R libraries. The analysis process is summarized in Figure 1.

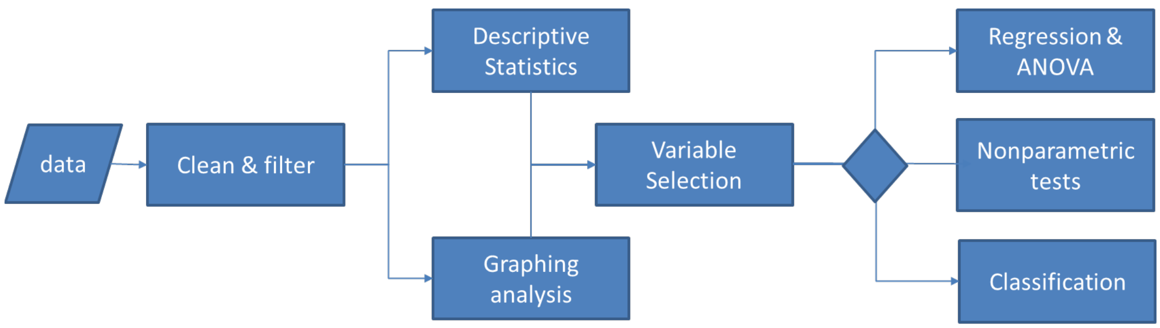

Figure 1. Research analysis flow

The outputs of the analyses were validated regression models for both cycle time (in months) and schedule change (percent change in cycle time since program start), acquisition strategy classifications and significant government and market-related factors.

Data collection

This research created several datasets. First was a MDAP dataset consisting of resources, programmatic, developmental and operational testing, maturity and schedule factors for MDAPs active between 2007 through 2018. The data was derived from publicly available data. Government sources included:

- Government Accountability Office (GAO) Annual assessments (GAO, n.d.),
- Director, Operational Test and Evaluation (DOTE) Annual Reports (DOT&E, n.d.),

- Publicly-released Selected Acquisition Reports (SARs) (OSD (AT&L), n.d.-b), and
- December SAR Summary reports on cost variances (OSD (AT&L), n.d.-a).

A total of 162 observations were recorded in an Excel spreadsheet, with 70 predictor variables in the dataset. Observations were selected for MDAPS with reports from both the GAO Annual assessments and DOTE Annual Reports. This reduced the quantity of observations, but ensured two independent assessments of program status. SAR data was used when available to supplement the GAO information. SAR summary report data was added to these reports to include cost variance information due to schedule or engineering changes.

A second file was created from annual DoD competition reports and metrics (Defense Pricing and Contracting, n.d.) consisting of contract award sums for the top 100 contractor and fiscal year between 2007 and 2018[54]. The data was used to identify the top 5 DoD contractors by award value and to quantify overall DoD market competition.

Two large files were created from the Federal Procurement Data System (USA.gov, n.d.). This data includes information such as contract numbers, award quantities and dates, vendor names, and product and service description codes for the top 5 contractors. One file contains competed award records and the second file non-competed awards for the top 5 contractors between 2007 to December 2020. Each file contains over 30,000 records between 2007 to 2018. These files were used to characterize market conditions and competition.

DoD budget documentation and procurement appendices (Under Secretary of Defense (Comptroller), n.d.) were used to obtain procurement quantities, budgets, and average procurement unit costs for DoD acquisition programs with nonzero procurements between 2007 and 2020.

Finally, a small dataset of annual revenues and net earnings for the top 5 contractors was created from corporate reports submitted annually to the Securities and

[54] This file has 288 different named contractors; not all stayed within the top 100 between 2007-2018.

Exchange Commission. All datasets created were saved in comma-separated variable formats and were submitted with the report.

Predictor and response variables

Three DoD outcomes and a categorical predictor were selected as response variables and are listed in Table I.

Table I. Response Variables

Variable ID	Description	Source	Notes	Type
Cycle.Mo	cycle time in months	GAO	derived if reported as NA by GAO	continuous
Cy.Mo.PCT	Percent change in cycle time since program start	GAO		continuous
Q	Cycle time quartile	Calculated		categorical
LN.P_no	Natural log transform of P_no (Table II)	Calculated	LN(P_no + 1)	continuous
LN.UC.M	Natural log transform of UC.M (Table II)	Calculated	LN(UC.M + 1)	continuous

Significant[55] ($\alpha = 0.05$) cycle time-related factors are highlighted in *green* and described in Table II.

[55] Significance was determined by regression analyses shown in section 4.1

Table II. Significant predictor variables

Variable ID	Description	Source	Notes	Type
RD.M	research and development (R&D) funding, $M	GAO		continuous
LN.RD.M	Natural log transform of RD.M	Calculated	LN(RD.M+1)	continuous
P_no	procurement quantity objective	GAO		continuous
UC.M	Reported unit cost, $M	GAO		continuous
SW.Gp	SW development model (0=waterfall, 1=incremental, 2=other)	GAO/SAR	0 = waterfall 1= Agile/ incremental 2 = hybrid/other/none	categorical
ENG.Gp	Cost variance due to Engineering changes	DoD	0 = less than 0 1= equal to 0 2 = greater than 0	categorical
Joint	Joint program (1=yes)	GAO/SAR		binary
DEPEND	Program depends on other programs (1=yes)	GAO/SAR		binary
COML	Program depends on commercial technologies (1=yes)	GAO/SAR		binary
Reuse	Program reuses military technologies/systems (1=yes)	GAO/SAR		binary
Fin_Uns	> 10% change in funding (since start or year to year) (1=yes)	GAO/SAR		binary
CTES	Number of reported critical technology elements	GAO/DOTE	GAO/DOTE report	continuous
ACQ_P	Acquisition model	SAR/GAO	SAR; DODD 5000.02	categorical
SVC	Acquiring Service	GAO	Army, Navy, Air Force, DoD	categorical
INTEG	System integration issues in test	DOTE	(i.e. fit) (1=TRUE)	binary
Restr	Program restructured (1=yes)	Calculated	GAO or SAR	binary
NM	Program incurs a Nunn-McCurdy Breach (1=yes)	GAO/SAR	GAO or SAR report	binary
Type	Commodity Type	GAO/SAR	AIR, C3I, GND, SHIP, MSL/SPACE	categorical
PM.Oth	External PM influences reported	GAO	GAO	binary
UC.M.PCT	Percent change in UC.M	GAO	GAO	continuous
LN.UC.M	Natural log transform of UC.M	Calculated	LN(UC.M+1)	continuous
P_no.PCT	Percent change in P_no	GAO	GAO	continuous

A full data dictionary is provided with the datasets and in the Appendix. Finally, Table III provides a set of predictor variables related to contract data.

Table III. Market and contractor predictors

Variable ID	Description	Source	Notes	Type
AO	Contract action obligations ($)	FPDS	FPDS.gov	continuous
CA	Contract action (count)	FPDS	FPDS.gov	continuous
PRIME	Prime contractor designator	various	e.g., BA, GD, LMT, NOC(NGC), RTN	categorical
RD.INTENSITY	MDAP research intensity	calculated	RD.M/(RD.M+P.M)	continuous
PSC Type	Product and Service Code	FPDS	P= product S= Service	categorical
PSC Code	PSC Code from contract	FPDS		categorical
REVENUE.M	Reported annual Revenue ($M)	10-K	Or Sales	continuous
EARNINGS.M	Reported annual Net Earnings ($M)	10-K	Or net income	continuous
PROFIT.PCT	Percent profit	Calculated	EARNINGS.M/REVENUE.M	continuous

Statistical methods

This research assumed three response variables representing DoD functional objectives: cycle time (Cycle.Mo), procurement quantities (LN.P_no), and unit cost (LN.UC.M). Ensemble modeling (Ray, 2017) using the R randomForest package (Liaw, 2018) was used to identify important predictor variables. These variables were used to create linear regression models for the above response variables by eliminating those with variable inflation factors greater than 5, and then with p-values greater than 0.05. Each model was inspected to ensure regression assumptions were satisfied.

The data set was cleaned, filtered and tested for consistency, correlation, and independence (Marshall & Russell, 2018). Some observations did not report values as they were withheld due to security concerns or because the data was under revision at the time of review. In such cases, the entry was calculated from other sources. Values were recorded as "0" if the GAO reported it as NA and there was no alternative source of estimate. The variables were analyzed using descriptive statistics to identify minimum and maximum values. These were inspected by variable for correct entry and tested using Dixon's r22 outlier test (Minitab, n.d.-a).

Observations and their distributions were characterized by means, medians, standard deviations, skew and kurtosis and proportions (for categorical variables). Spearman's rho (Minitab, n.d.-c) was used to calculate correlation coefficients and significance for continuous and categorical variables. Graphing was used to compare response variable distributions[56] against normal distributions[57]. As the research was considering a multivariate model, the Mahalanobis distance (Minitab, n.d.-b) was used to identify outlier observations. While several outliers were identified, no observations were removed from the dataset for this analysis.

Random forest ensemble modeling was used to estimate variable importance (VI) and regression model performance (Grömping, 2009). Random forests (RF) have been noted to bias VI towards continuous variables, so conditional random forest

[56] Such as cycle time.
[57] This is helpful when evaluating if there is a difference in sample distributions for various factor categories.

modeling was applied to identify if any categorical variables should be considered as important factors to consider for a regression model.

Parsimonious regression models were developed in Minitab and SPSS relating cycle time to predictor variables. The models were adjusted to maximize the predicted coefficient of determination (R-sq(pred)) with the fewest number of terms. Anderson-Darling tests were used to verify normality assumptions. The residual plots were inspected to identify any trends and verify constant variance assumptions.

As the dataset contains outliers and predictors did not typically exhibit normal distributions, nonparametric methods such as Mood's Median test were used to assist in identifying significant factors and relationships. Chi-square tests of categorical variables by cycle time quartile were used to test for association and independence of categorical factors to shorter or longer cycle times.

Competed and non-competed procurement data for the top 5 contractors and DoD procurements between 2007-2018 were used to characterize market conditions and competition. Research and development and procurement funding was used to calculate research intensity for the top 5 contractors as a measure of innovation. Descriptive statistics, t-tests and ANOVA analysis, and graphical analysis were used to assess market competition trends. Text search methods were applied to Selected Acquisition Reports to identify MDAPs with explicit streamlining or tailoring modifications.

Quantitative methods were used to classify acquisition strategies using resource, structural, and external factors. K-means clusters were created in Minitab, and tested using random forest classification. Two-sample t-tests, and ANOVA tests were used to identify statistically significant differences of functional objectives between groups. Regression models were created to interpret differences in significant variables on functional objectives. These results were used to compose a decision framework based on functional objectives.

Research variable selection

Variable importance was ranked using three R random forest packages: randomForest, cforest (Hothorn, 2020), and VSURF (Genuer, 2019). While the estimators are different, the larger the value, the more important the variable to the ensemble model. As an example, Table IV shows the top 10 variables for cycle time (Cycle.Mo) regression.

Table IV. Top 10 variables using different random forest packages

randomForest	%IncMSE	cforest	CRF_VI	VSURF	VI.mean
UC.M.PCT	14.16	P_no.PCT	144.57	UC.M.PCT	394.57
P_no.PCT	11.92	P.M	97.85	P_no.PCT	370.78
RD.M	9.65	RD.M	86.23	RD.M.PCT	195.98
CC.Sked_1	8.48	LN.RD.M	82.93	CC.Sked_1	192.85
RD.M.PCT	8.40	CC.Sked_1	79.14	RD.M	155.89
LN.RD.M	8.09	UC.M.PCT	77.06	LN.RD.M	153.57
LN.P_no	7.21	*Restr*	41.82	LN.P_no	79.37
UC.M	6.96	*Fin_Uns*	37.95	Eng	76.86
Eng	6.37	*RMA*	35.53	LN.UC.M	66.24
SoS_part	6.35	CC.Sked	35.39	UC.M	65.72

The cforest package promoted three categorical factors (in italics) into the top 10 variables. The VSURF model fit (R-sq(adj), or adjusted coefficient of determination) was 0.71 with an MSE of 636.1, but required 20 predictors to achieve this result.

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Results and Analysis

Significant predictors of program cycle time and schedule change

Cycle time Regression results

In order to validate the regression model performance, a random draw of 44 of 162 (27 percent) of the database observations was set aside as a validation dataset. A manual step-wise regression on the remaining 118 observations was performed starting with identified important variables from random forest results. Predictors with p-values greater than 0.05 were removed one at a time. Variance inflation factors (VIFs) were all less than 5, indicating no collinearity issues. The final model satisfied all regression assumptions, and is

$$Cycle.Mo = -10.2 + 18.98 * LN.RD.M + SW.Gp + Joint + DEPEND + Reuse + COML + Fin\_Uns \quad (1)$$

where

Cycle.Mo is MDAP cycle time in months (response or dependent variable);
LN.RD.M is the natural log of the MDAP research and development budget in millions;
SW.Gp = -27.38 for Agile, -24.2 for hybrid or N/A, 0 for waterfall approaches;
Joint = -15.02 if MDAP is designated as Joint, otherwise 0;
DEPEND = +16.1 if MDAP depends on another MDAP, otherwise 0;
Reuse = -19.42 if in-service technology is re-used, else 0;
COML = -23.99 if MDAP uses commercial technology to deliver capability; else 0;
Fin_Uns = +26.79 if more than 10% change in funding since program start, else 0.

Strategy factors with negative coefficients (highlighted in red) are associated with *reducing* cycle time. These were execution as a Joint program (Joint), use of an agile or incremental software development strategy (SW.Gp), use of commercial technologies (COML), and re-use of developed military technology (Reuse).

The amount of research and development (R&D) funding (LN.RD.M) planned for the program is directly related to cycle time – the more R&D funding, the longer the cycle time. In this model, having critical dependencies on other MDAPs (DEPEND) is associated with longer cycle times (positive coefficient). Financial instability (Fin_Uns) is typically not an intentional part of an acquisition strategy, but if it occurred was associated with longer cycle times.

Prediction performance was validated using the withheld sample. The adjusted R-squared (r-sq(adj)) for the trained regression model is 62.74 percent; the predictive R-squared (r-sq(pred)) is 57.91 percent. The mean predicted cycle time is 9.1 months longer than observed cycle time and is shown in Figure 2.

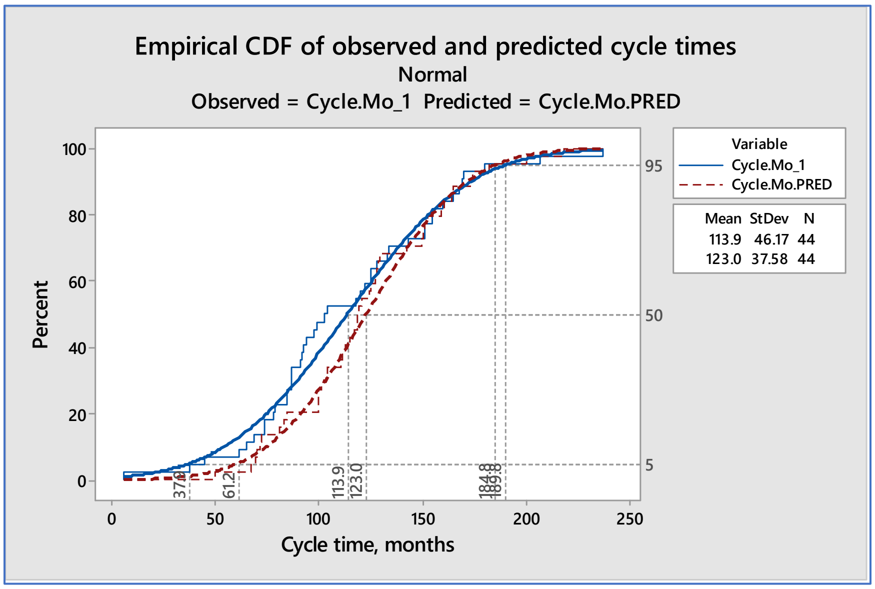


Figure 2. Trained model prediction accuracy

Predicted cycle times set an upper bound for cycle time values for programs with shorter cycle times. This over-prediction of program cycle time provides a conservative margin.

Schedule change regression results

The same process as above was used to create a schedule change (percent change in cycle time, Cy.Mo.PCT) regression model. The final model satisfied all regression assumptions, and is

$$Cy.Mo.PCT = -0.0955 + 0.01979*P.M.PCT + 0.02706*CTES + Fin\_Uns + ACQ\_P + SVC + Restr + INTEG + NM \quad (2)$$

where

P.M.PCT = the percent change in procurement budgets since program start;
CTES = the number of critical technology elements (identified by GAO) at start;
Fin_Uns = +0.1230 if budgets change by more than 10 percent, else 0;
ACQ_P = the DoDI 5000.02 procurement model: 0 if model 1, +0.3184 if model 2,
- 0.023 if model 4, +0.0110 if model 5, +0.0429 if model 6;
SVC = 0 if AF - 0.0765 if Army - +0.0218 if DoD, +0.1741 if Navy;
Restr = +0.1301 if restructured, else 0;
INTEG = - 0.1007 if there are system integration issues found during testing, else 0; and
NM = +0.1258 if MDAP has a Nunn-McCurdy breach, else 0.

Schedule change is linearly related to percent change in procurement budgets and the number of Critical Technology Elements. Acquisition model was a small factor unless the MDAP was software intensive (model 2), which was associated with significant schedule growth. Early discovery of integration issues (INTEG) reduced schedule change. Service (SVC) was significant for Army (reduced schedule change) and Navy (schedule change growth was driven by ships, primarily CVN-78, DDG-1000, and LCS). MDAP financial instability (Fin_Uns), restructuring (Restr) and occurrence of a Nunn-McCurdy breach (NM) were all associated with schedule change growth (longer cycle times).

Prediction performance was validated using the withheld samples. The model R-sq(adj) is 66.99% with an R-sq(pred) of 59.28%. Prediction standard error is 0.07853, and the MSE between actual and predicted values was 4.3 percent (0.04268). Results are in Figure 3.

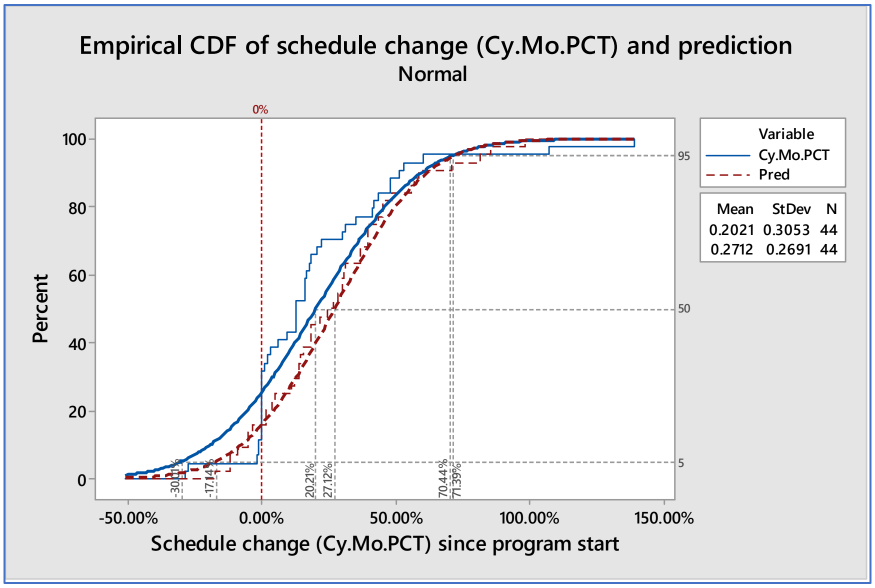


Figure 3. Percent schedule change prediction validation results

Predictor change with acquisition strategies

Different combinations of predictors were used to predict group or cluster association using K-Means analysis. Typical accuracy rates (probability of correct classification) were less than 30% without use of the development and production categorical variables. The random forest classification package (randomForest) was used to classify observations into cycle time quartiles. Table V shows the out-of-bag (OOB) randomForest model classification results.

Table V. RandomForest classification results

OOB	Predicted quartile (Q)					
Q True	Q1	Q2	Q3	Q4	TPR	FNR (ty II)
Q1	17	4	0	1	77.3%	22.7%
Q2	5	14	2	0	66.7%	33.3%
Q3	0	3	18	3	75.0%	25.0%
Q4	1	1	5	7	50.0%	50.0%
FPR (ty I)	26.1%	36.4%	28.0%	36.4%	69.1%	

In Table V, TPR is the true positive rate, FNR is the false negative rate, and FPR is the false positive rate. The classification model correctly classified over 77% of 1st quartile observations. The top 10 random forest predictors for cycle time from the

VSURF package are compared with the variable usage frequencies for randomForest classification in Table VI.

Table VI. Random Forest top 10 cycle time variables means and usage frequencies

VSURF	VI.mean	randomForest	freq
UC.M.PCT	394.57	UC.M.PCT	481
P_no.PCT	370.78	RD.M.PCT	454
RD.M.PCT	195.98	LN.RD.M	449
CC.Sked_1	192.85	LN.P_no	372
RD.M	155.89	CC.Sked_1	368
LN.RD.M	153.57	RD.INTENSITY	366
LN.P_no	79.37	RD.M	357
Eng	76.86	P.M	348
LN.UC.M	66.24	CC.Sked	344
UC.M	65.72	P.M.PCT	340

The regression predictors from VSURF match 7 of 10 of the randomForest quartile (Q) classification predictors. Descriptive statistics of the 1st quartile random forest predictors are summarized in Table VII.

Table VII. First quartile cycle time top 10 RF predictor statistics

Variable	Mean	sigma	Min	Median	Max	IQR
UC.M.PCT	0.01	0.24	-0.84	0.00	0.58	0.18
RD.M.PCT	0.15	0.33	-0.19	0.03	1.61	0.20
LN.RD.M	6.54	1.48	1.48	6.88	8.88	1.88
LN.P_no	6.57	2.56	1.95	5.78	11.18	4.06
CC.Sked_1	28.60	138.60	-282.40	0.00	486.90	2.10
RD.INTENSITY	0.21	0.21	0.00	0.17	0.80	0.22
RD.M	1585.00	2100.00	3.00	975.00	7167.00	1561.00
P.M	10010.00	11360.00	175.00	4858.00	35513.00	10754.00
CC.Sked	-8.53	39.40	-157.90	0.00	127.50	20.80
P.M.PCT	0.37	0.81	-0.71	0.00	2.59	0.61

The randomForest model correctly predicted the cycle time quartile 69.1 percent of the time, and the ten most significant factors were resource and resource change predictors. Acquisition strategy decisions include resource factors, and the proportion of R&D funds to R&D and procurement funds (RD.INTENSITY) is an example of such a decision.

Structural factors may be statistically significant, but not obvious from a random forest model. For example, Table VIII summarizes the results of testing the association of DoD acquisition model[58] to cycle time quartiles.

Table VIII. DoD acquisition plan by quartile

	Q1	Q2	Q3	Q4	P
1	21	20	22	26	0.000
2	0	1	2	6	
4	4	0	0	2	
5	10	16	17	4	
6	8	1	1	1	

xx over-represented in Q

xx under-represented in Q

p is the $\chi 2$ likelihood ratio test p-value

The table p-value indicates that there is a statistically significant association between cycle time quartiles (columns) and DoD acquisition model (rows). Summing across a row provides the total number of that program model in the sample set. the color code indicates if a factor is over- (pink) or under- (green) represented in a quartile. Model 1, "hardware intensive program", counts are as expected in each quartile, while model 2, "software intensive program" is under-represented in the 1st quartile, and over-represented in the 4th quartile, implying such programs tended towards longer cycle times. Model 4, "accelerated acquisition program", is over-represented in the 1st and 4th quartiles[59]. A hybrid software-dominant acquisition model (model 6 in the table) is under-represented in the 4th and over-represented in the 1st quartiles.

Cycle times and technical maturity

Technology and design maturity were not significant at α = 0.05 in the trained regression models. The dataset was divided into groups to understand how technology and data maturity as assessed by the GAO are related to cycle time. The first group, designated 00, is when the GAO assessed that *neither* the system technology or design

[58] Such as Model 1, "Hardware Intensive Program" (Kendall et al., 2015). This is factor ACQ_P, which is not in Table VII.

[59] What is not shown is that the two 4th quartile MDAPs had cycle times of 87 and 133 months (at the low end of the quartile).

were mature[60]. The second group, designated 11, is when the GAO assessed that *both* the system technology and design were mature. These choices (whether to use mature technologies or designs) are made by the program office when planning the MDAP. Table IX summarizes cycle time statistics between these groups.

Table IX. Subset summary Cycle time statistics

Dataset	N	Mean	SE Mean	sigma	Min	Q1	Q3	Max	IQR
Full set	162	118.93	3.87	49.30	0	81.75	154.25	248	72.5
00 (not mature)	61	123.33	6.43	50.23	6	83.5	155	248	71.5
11 (Both mature)	63	123.14	6.56	52.03	0	87	159	237	72

Linear regressions for the 00 and 11 datasets were developed using the same process as the trained model; however, no observations were withheld for prediction validation. The cycle time linear regression for the subset of observations where the GAO assessed *neither* technology or design as mature (the immature or 00 model) is

$$Cycle.Mo = 92.6 + 0.001097*RD.M + 17.46*UC.M.PCT + 5.12*LN.UC.M + COML \quad (3)$$

where

Cycle.Mo is MDAP cycle time in months (response or dependent variable);
RD.M is the MDAP research and development budget in millions;
UC.M.PCT is the GAO-reported percent change in unit cost since program start (100% change= 1.0, and can be negative);
LN.UC.M = the GAO-reported unit cost in millions; and
COML = -24.43 if MDAP uses commercial technology to deliver capability; else 0.

Over 38 (38.29) percent of the model variance is explained by LN.UC.M and UC.M.PCT. The regression model includes a resource-related factor (RD.M) and a program structural factor (COML). This provides evidence that such decisions are important to program cycle time outcomes for development-driven programs.

[60] GAO assessed that key knowledge points were achieved at or prior to Milestone B (technology mature) or Critical Design review (Design Mature).

The statistically significant factors for a cycle time regression change following technology and design maturity. The cycle time linear regression where the GAO assessed *both* the technology and design as mature (the mature or 11 model) is

$$Cycle.Mo = 91.08 + 0.003143*RD.M - 58.2* P\_no.PCT + Joint + PM.oth \quad (4)$$

where

Cycle.Mo is MDAP cycle time in months (response or dependent variable);
RD.M is the MDAP research and development budget in millions;
P_no.PCT is the percent change in procurement quantities since program start (100% change= 1.0, and this value can be negative)
Joint = -86.3 if MDAP is designated as Joint, otherwise 0;
PM.oth = 26.74 if MDAP has outside program office direction on program execution,
else 0.

Nearly 27 percent of model variance is explained by RD.M. A positive change in procurement quantities is related to lower cycle times. Joint designation is related to lower cycle times for MDAPs with mature system technologies and designs.

Cycle time model 1 predictive performance was validated using withheld samples. The maturity models (3 and 4) were not tested against a withheld sample. Model 3 and 4 predictive R-sq values are provided for comparison purposes. The performance of the Cycle time models is summarized in Table X.

Table X. Cycle time model performance summaries

Model	Eqn ()	S	R-sq	R-sq(adj)	R-sq(pred)
Trained	(1)	30.81	65.29%	62.74%	57.91%
00	(3)	33.30	58.98%	56.05%	52.46%
11	(4)	31.32	66.10%	66.76%	58.94%

Cycle times show a dependence on research and development funding (RD.M or LN.RD.M) for the above cycle time models. Predictive factors change as system technology and design matures during MDAP execution. Unit cost and cost changes (LN.UC.M and UC.M.PCT) were significant model factors when system technology and design were assessed as immature (00 model). Cycle times (when system technology and design were assessed as mature) showed a dependence on procurement quantity change (P_no.PCT). Additionally, the both the trained and mature (11) models showed at least one factor related to issues beyond program office control (PM.oth, Fin_Uns).

Unit cost results

A manual step-wise regression on the same 118 observations was performed as above for unit costs, again starting with identified important variables from random forest modeling. A single factor was sufficient and satisfied all regression assumptions, and is

$$\mathit{LN.UC.M} = 8.545 - 0.8133 * \mathit{LN.P\_no} \tag{5}$$

The r-sq(pred) is 72.08 percent. As before, the model prediction performance was validated using the withheld sample. The MSE between actual and predicted values was 1.517. Results are in Figure 4.

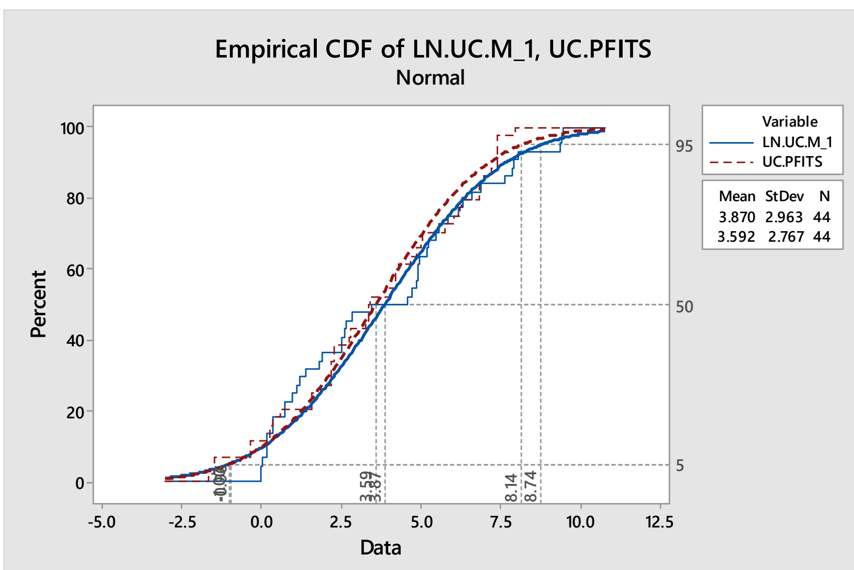


Figure 4. Unit cost model validation results

Procurement quantity results

Unit costs were graphically compared to program research and development and procurement budgets and procurement quantities. These predictors were transformed into natural logarithmic variables due to their ranges, and are shown in Figure 5.

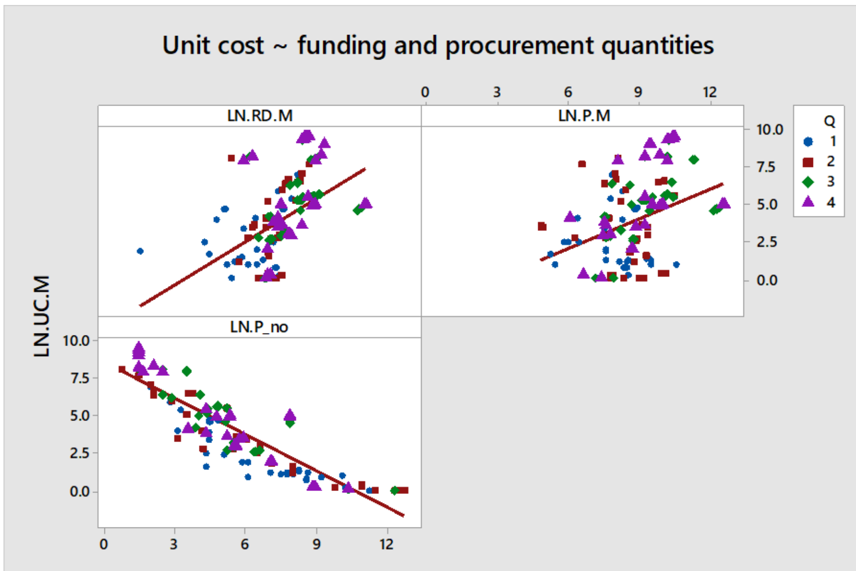


Figure 5. Unit costs versus budgets and procurement quantities

The strongest relationship is between unit cost (LN.UC.M) and procurement quantities (LN.P_no). A linear regression following the above approach was performed for procurement quantities. Results are in Figure 6.

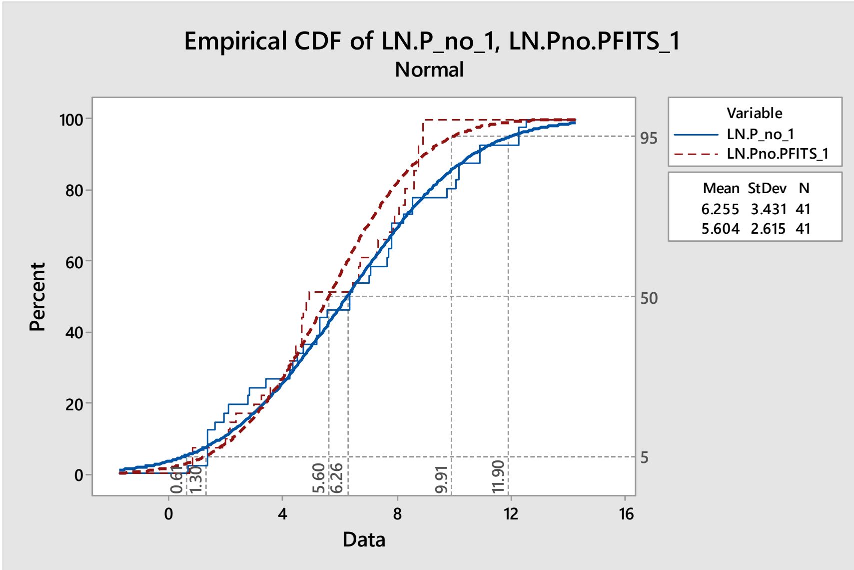


Figure 6. Procurement quantity model validation results

The model would not satisfy regression assumptions without trimming outliers. After trimming outliers, a single factor model satisfied all regression assumptions, and is

$$LN.P\_no = 8.919 - 0.8605\ LN.UC.M \tag{4}$$

As before, the model prediction performance was validated using the withheld sample. The MSE between actual and predicted values was 2.368. The r-sq(pred) is 76.83 percent. These two models illustrate the strong relationship between unit cost and procurement quantities.

Acquisition strategy decision frameworks- planning phase

Program offices are capable of balancing competing issues such as urgency of need, affordability objectives, and unquantified schedule, cost and performance margins into program plans. Several researchers provided substantiated recommendations for acquisition program functional objectives[61] and feasible approaches[62].

[61] Mortlock, Jovel and Jain, Browning, and Farmer in particular. See also the work by Rendon on program office matters.

[62] Tate, Graviss, and Syeda as examples.

Sometimes, exquisite requirements and system of systems architectures have unrecognized interactions or dependencies. A critical program planning task is identifying and managing risks associated with these interactions and dependencies. Interaction plots, a type of graphical analysis, help identify factor interactions for further analysis. An example using the research data set for AIR type systems is shown in Figure 7.

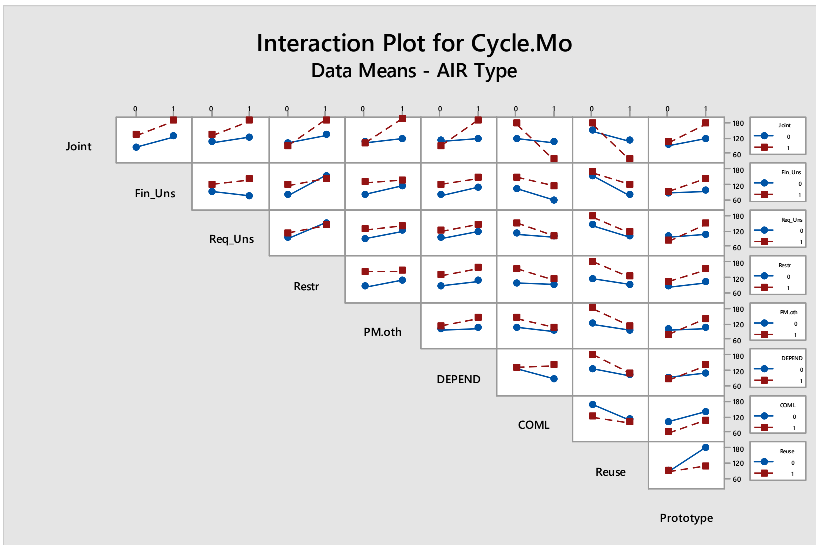


Figure 7. Cycle time interaction plot for AIR systems

In this interaction plot, non-parallel lines indicate where cycle time outcomes change[63] for different factor levels. Crossing lines indicate strong interactions are between MDAP strategy factors such as Joint designation (Joint) and use of commercial technology (COML) or technology reuse (Reuse). These are shown in equation (1) as differences in coefficients. Restructuring a program (Restr) in execution has interactions with related to Joint, financial instability (Fin_Uns), requirements instability (Req_Uns), and prototype use during development (Prototype). Figure 8 shows AIR systems interactions for operational testing factors.

[63] The interactions must still be tested for statistical significance.

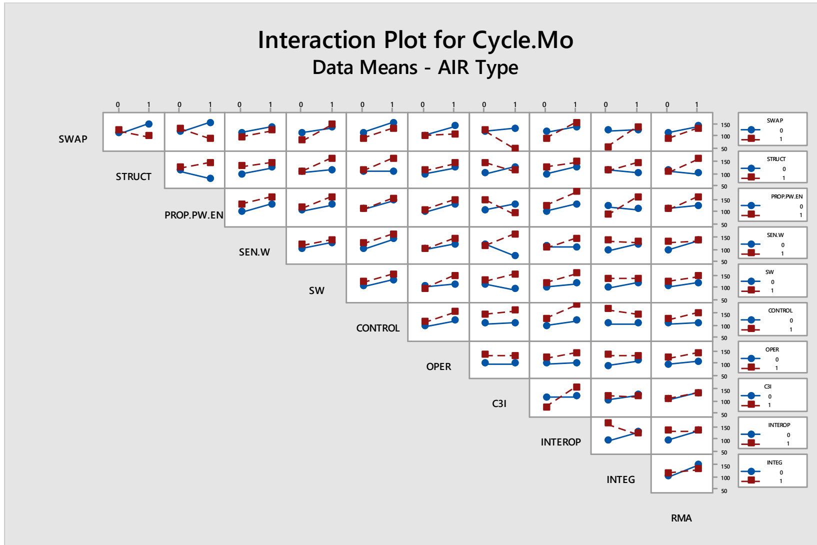


Figure 8. AIR systems operational testing factor interaction plot

Again, non-parallel lines indicate where operational testing factors interacted, such as between size, weight and power issues (SWAP), structural issues (Struct), or propulsion power and energy (PROP.PW.EN). As a comparison, a similar interaction plot for Command, Control, Communications and Intelligence (C3I) is shown in Figure 9.

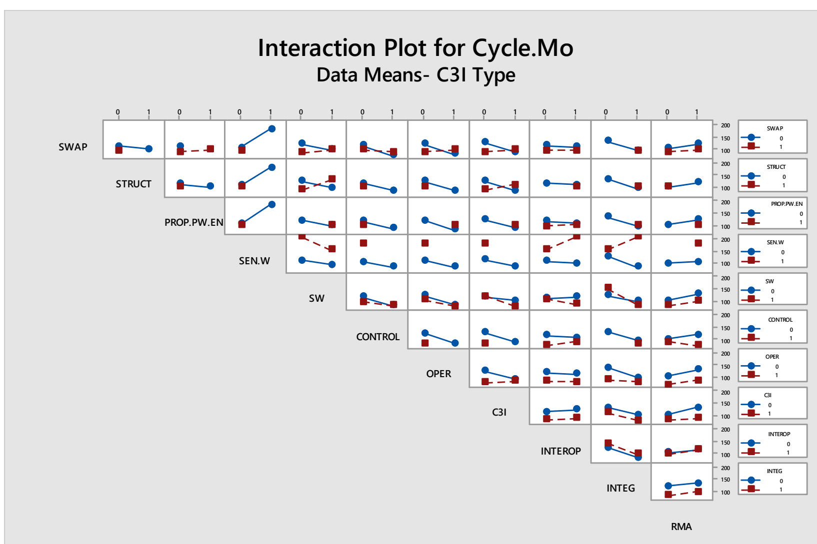


Figure 9. C3I operational testing interaction plot

The C3I plot (Figure 9) has different factor interactions than the AIR plot (Figure 8). This suggests program offices should can use such methods to identify potential development and testing risks associated with historical type-specific interactions.

Decision frameworks for in-execution program changes

The research shows that initial decisions, such as use of commercial technology or reuse of existing technology, are associated with reduced cycle times. When program technologies are immature, strategies using commercial technology and lowering unit cost are likely to lower cycle times. If the product is mature, then increasing production quantities is likely to lower cycle time (sooner to IOC). The program is assumed to mature over time, and the acquisition strategy analysis showed example factor interactions during planning and execution.

Acquisition programs change over time. Some changes are statutory, as in response to a Nunn-McCurdy breach. Some changes are in response to changing priorities. A decision framework is provided to help identify prior programs with similar features, illuminating how others addressed a similar problem.

This research identified a limited set of factors affecting cycle time outcomes. It assumes knowledge of the current functional objective (cycle time, unit cost, procurement quantities) and value. The program office should include a new estimated program state, a changed functional objective or target, their assessment of the current risk register and an understanding of key technical and programmatic interactions which will inform the estimated revised outcome. Program offices would search existing acquisition information systems[64] to identify promising prior programs. Case studies and data from these programs, in concert with predictive models (a project schedule or system dynamics schedule model[65]) provide context and ideas for potential approaches with known results. The key search questions are summarized in Figure 10.

[64] As an example, the Defense Acquisition Management Information Retrieval (DAMIR) System.
[65] For a system dynamics model overview, see Cantwell et al., Dynamic Consequences of Cost, Schedule, and Performance Within DoD Project Management, *Def Acq Res J* , Vol 20, Issue 1.

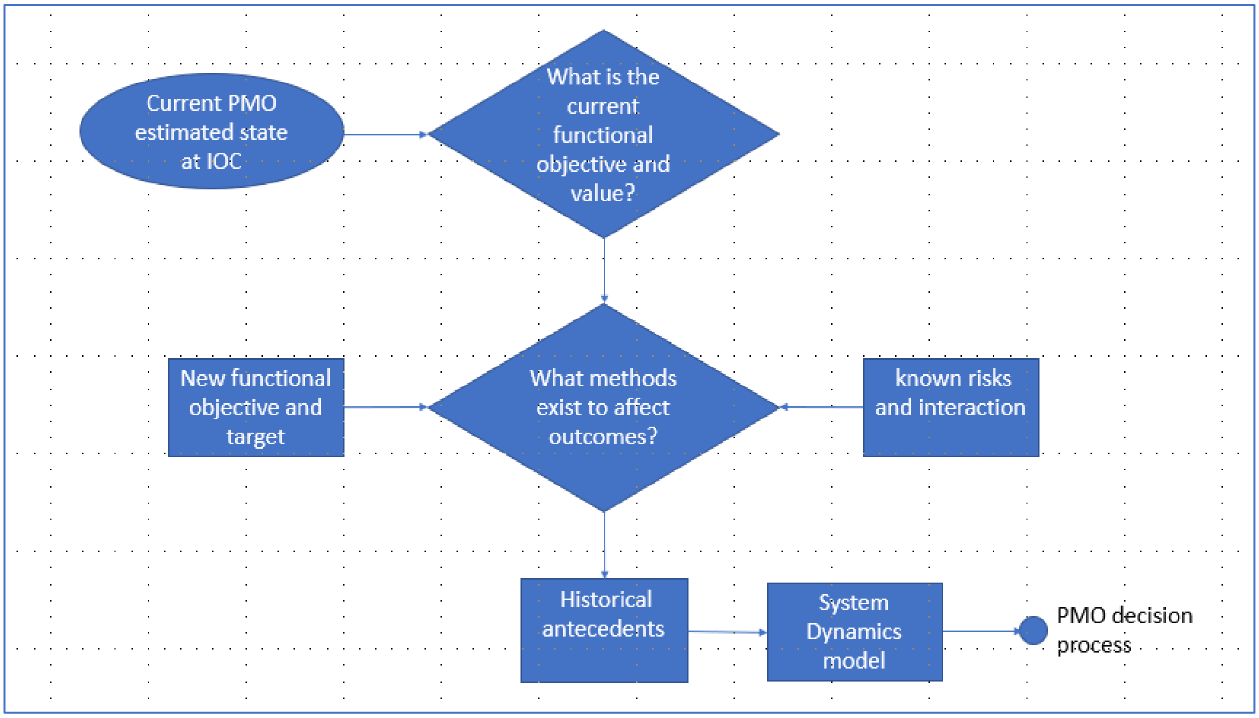


Figure 10. In-execution decision framework

Historical antecedents are identified by dataset filtering. As an example, a subset of the research dataset[66] is filtered using the top three cycle time variable importance predictors, and the program office wants to reduce cycle time for an AIR system. The first question is *"Do you want to reduce cost?"*, splitting when MDAP percent change in unit cost (UC.M.PCT) is less than the dataset median value. The output is provided by commodity type as shown in Figure 11.

[66] The dataset is subsetted for simplicity to contain only the top 5 DoD contractors in Figures 11-13.

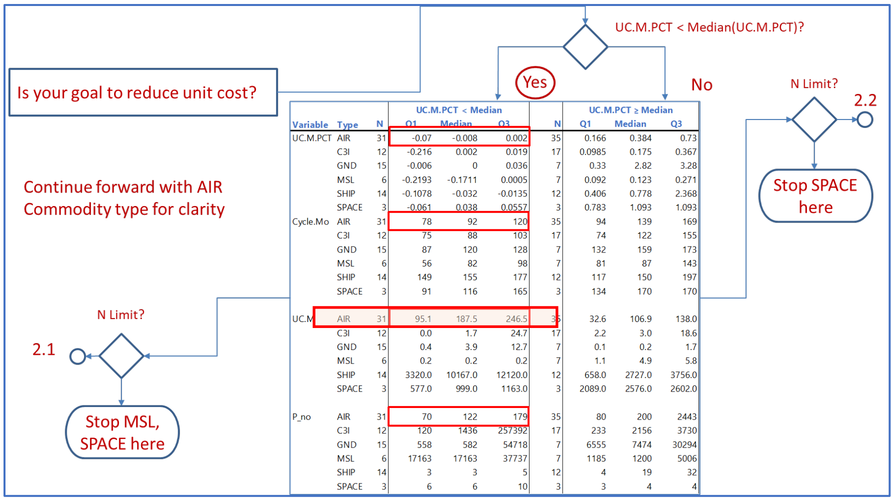


Figure 11. Unit cost reduction decision point

In Figure 11, SPACE is highlighted to indicate that there are few samples in the sort, and the decision tree for SPACE should stop here. The table shows the median cycle time value (62 months), bounded by the 1st and 3rd quartile values (78-120 months) to minimize outlier importance. Program offices may use the mean and standard deviations to set confidence intervals. The second question is *"Do you want to reduce procurement quantities?"*, which splits MDAP observations on the median percent change in procurement quantities for the data subset and is shown in Figure 12.

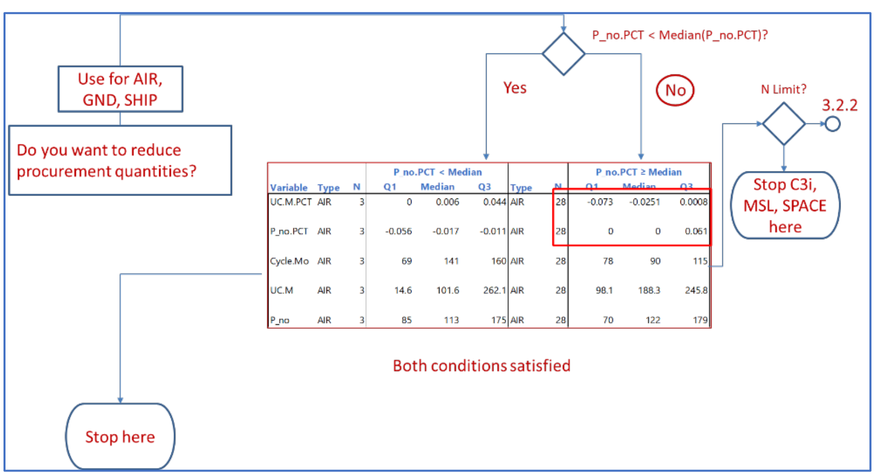
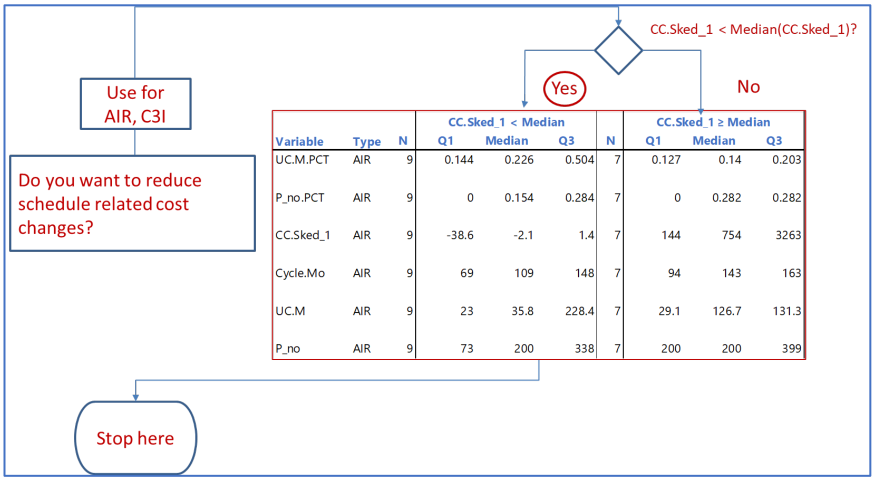


Figure 12. Procurement quantity change decision point

Note the change in AIR cycle times, for a small reduction in procurement quantities. The final decision question is *"Do you want to reduce schedule-related cost changes?"*, where the results are shown in Figure 13.



Variable	Type	N	CC.Sked_1 < Median Q1	Median	Q3	N	CC.Sked_1 ≥ Median Q1	Median	Q3
UC.M.PCT	AIR	9	0.144	0.226	0.504	7	0.127	0.14	0.203
P_no.PCT	AIR	9	0	0.154	0.284	7	0	0.282	0.282
CC.Sked_1	AIR	9	-38.6	-2.1	1.4	7	144	754	3263
Cycle.Mo	AIR	9	69	109	148	7	94	143	163
UC.M	AIR	9	23	35.8	228.4	7	29.1	126.7	131.3
P_no	AIR	9	73	200	338	7	200	200	399

Figure 13. Schedule-related cost variance decision point

In this case, as the dataset contained only the top 5 subcontractors, the mean and average AIR cycle times are higher (106.9 and 109 months respectively) than when the same process is applied to the full dataset. This indicates that other AIR-type MDAPs had different relevant results (in this case L3 and Sikorsky) that were excluded by the initial dataset subsetting.

Streamlining and predictors

Program process changes are reported as tailored, modified, or streamlined processes. These changes occurred at program start and in execution. The publicly released DoD Selected Acquisition Reports[67] (SARs); 54 were identified with streamlining type changes. Figure 14 shows the count of programs by commodity type.

[67] Available at https://www.esd.whs.mil/FOIA/Reading-Room/Reading-Room-List_2/Selected_Acquisition_Reports/ .

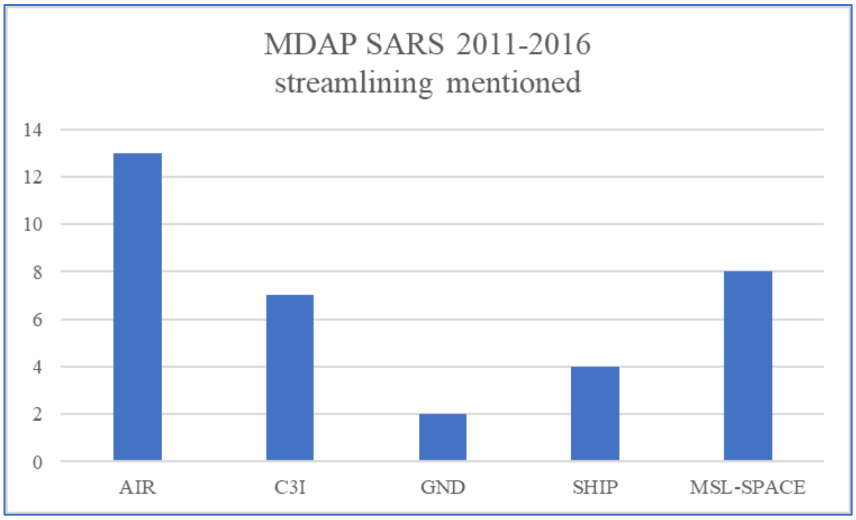


Figure 14. MDAPs with identified streamlining/tailoring

The results were filtered to remove streamlining references not related to process changes. Approximately 1/3 of programs in this research intentionally modified processes either during program development or in execution. Most streamlining (program tailoring) actions occurred during program development. Restructuring actions during execution were intended to slow cost or schedule growth and included:

- eliminating redundant systems engineering and program management support,
- adopting commercial manufacturing processes, and shifting to incremental product delivery,
- working with contractors to reduce overhead costs,
- tailoring certification processes, and flight-test mission tailoring,
- reliability improvements through contractor and government teaming (capability sharing), and consolidating proposed supply chains, and
- aligning specific system upgrades to incremental production delivery blocks.

The effects of these action on cost or schedule growth were nor quantified within the program reports. These changes would likely be quantifiable by program offices using cost and schedule estimating tools, and could affect previously noted system cycle time interactions. Regressions of unit cost growth and procurement quantities growth percentages for the dataset MDAPs were not statistically significant between 2007 and 2018. A small (R-sq(Adj) = 11%) but significant (p=0.000) relationship was found for cycle time growth over this same interval. The overall acquisition system performance (based on the training dataset) was consistent with the cost and schedule growth trends reported by Kendall (Kendall, 2016).

Market condition effects on cycle time

Market factors – Competition between the top 5 defense contractors

These 5 contractors in order of defense market share are Lockheed Martin (LMT), Boeing (BA), General Dynamics (GD), Northrop Grumman (NOC) and Raytheon (RTN). They account for about 30 percent of DoD buys in between 2007 and 2018. An ANOVA test of DoD contract award dollar obligations[68] (R-sq(pred) = 77.72%) showed a significant difference between contractors (F-value 33.89, p-value 0.000). Games-Howell post hoc testing showed differences in means between LMT, BA, and the other three contractors (GD, NOC, and RTN). The relative market share of the five largest DoD contractors in Figure 15.

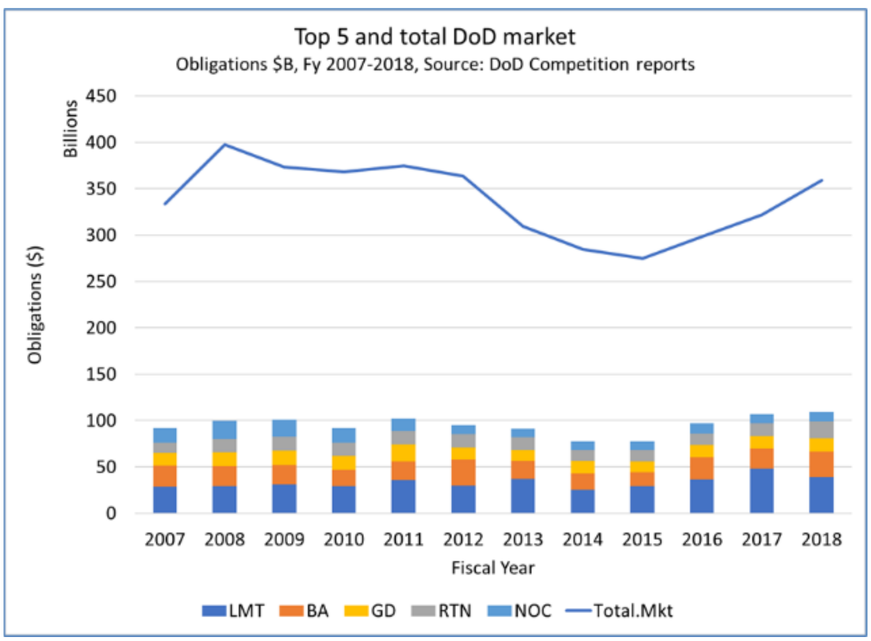


Figure 15. DoD contract actions, 2007-2018 (Source: FPDS.gov)

[68] An obligation is a current or future requirement for payment, such as a contract award.

The Top 5 contractors sell to the DoD within defined PSCs. There are over 2800 PSCs, and the Top 5 contractors and the DoD buy and sell within a subset of these PSCs. A contract award in a PSC means the bidder was competent at the time of award. Figure 16 shows which PSCs had multiple successful bidders from one or more top 5 contractors between 2007 to 2020.

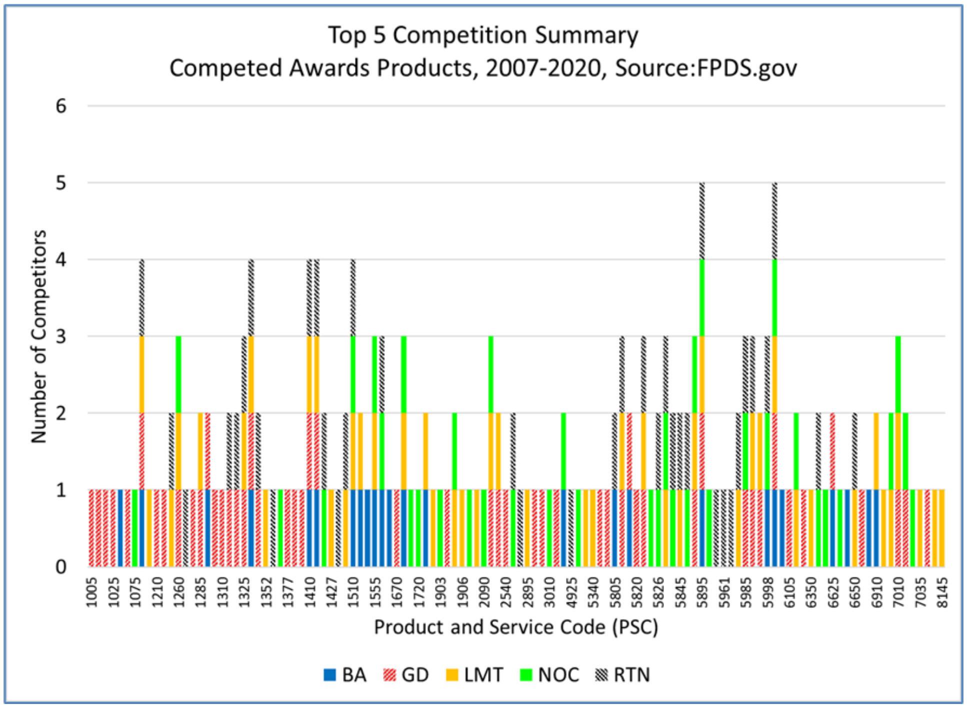


Figure 16. Top 5 DoD contractor competition summary (Source: FPDS.gov)

Note competition varies by PSC. Two PSCs for miscellaneous electrical, electronic and communications equipment have awards to all 5 contractors. Other PSCs had only one awardee between 2007 to 2020, indicating no effective competition within these PSCs, despite awards being competed. The number of Top 5 competitors by PSC for four market groups[69] are compared and shown in Figure 17.

[69] The groups are: 1) competed service-type PSC, 2) competed product-type PSC, 3) non-competed product-type PSC and 4) non-competed service-type PSC.

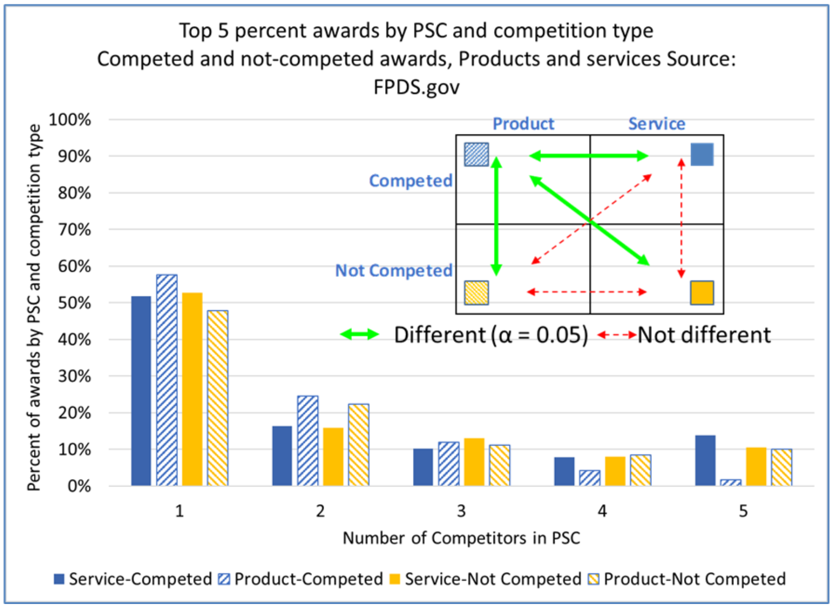


Figure 17. Competition distribution by PSC market

These markets include about 16 percent of all PSCs. Consistent with Figure 16, about half the PSC markets had only one bidder receive an award. Chi-square tests showed *service markets* with competition between the top 5 contractors, irrespective of whether the award was competed; *product* markets differed by competition and competed (or non-competed) awards. The differences in market competition shown in Figure 17 are quantified in Table XI.

Table XI. Chi-square test for market competition differences

reference	comparison	N	DF	Chi-Sq	P-Value
Service-Competed	Service-Not Competed	277	4	4.42	0.352
Service-Competed	Product-Competed	118	4	20.63	0.000
Service-Competed	Product-Not Competed	188	4	7.00	0.136
Product-Competed	Service-Not Competed	277	4	144.78	0.000
Product-Competed	Product-Not Competed	188	4	90.14	0.000
Service-Not Competed	Product-Not Competed	188	4	6.35	0.175

These results show that there are competitive differences in defense markets. As a more specific test of the effect of markets on cycle time, a sample of product PSCs representing each of these markets between 2007 and 2011 were drawn from FPDS data. Mean cycle times were represented by contract award period of performance (PoP) - the difference *in months* between the estimated contract completion date and the signing date. The results of 2 sample t-tests (Welch's method) of the differences in PoP means are in Table XII.

Table XII. Example award period of performance ("cycle time proxy") summaries

Market 1	Market 2	N1	N2	Mean1	Mean2	sigma 1	sigma 2	T	DF	p
Service-Competed	Service-Not Competed	1136	318	47.52	30.51	43.23	43.28	6.2	507	0.000
Service-Competed	Product-Competed	1136	276	47.52	36.42	43.23	79.92	2.23	315	0.026
Service-Competed	Product-Not Competed	1136	1540	47.52	50.51	43.23	59.65	-1.5	2673	0.133
Product-Competed	Service-Not Competed	276	318	36.42	30.51	79.92	43.28	1.1	409	0.273
Product-Competed	Product-Not Competed	276	1540	36.42	50.51	79.92	59.65	-2.79	332	0.006
Service-Not Competed	Product-Not Competed	318	1540	30.51	50.51	43.28	59.65	-6.98	595	0.000

These results show that mean PoPs are different for a PSC type (product or service) when awards are competed (or not competed). Similarly, mean PoPs for markets when awards are competed (or not competed) are different between PSC types.

Market factors – innovation

Two variables should be related to innovation – research and development budgets (RD.M or LN.RD.M) and research intensity (RD.INTENSITY). ANOVA (Welch's) tests of both variables by the top 5 contractors showed both were statistically significant *between* contractors[70]. Linear regressions using these two variables and the top 5 prime contractors showed:

Cycle.Mo = -59.2 + 20.46*LN.RD.M + PRIME (6)
where

[70] For the top 5 contractors: LN.RD.M F-value 9.69, p-value 0.000; RD.INTENSITY F-value 10.84, p-value 0.000.

PRIME = 0.0 for Boeing, 16.9 for General Dynamics, 19.42 for Lockheed Martin, 33.3 for Northrop Grumman and 43.7 for Raytheon.

In this model, LN.RD.M explains nearly 35 percent of model variance, and r-sq(pred) is 37.17%.

$$\text{Cycle.Mo} = 102.4 + 17.6{*}\text{RD.INTENSITY} + \text{PRIME} \tag{7}$$

where

PRIME = 0.0 for Boeing, 13.8 for General Dynamics, 23.8 for Lockheed Martin, 17.9 for Northrop Grumman and 23.1 for Raytheon.

In this model, RD.INTENSITY is not significant (p-value = 0.432) and r-sq(pred) is 3.98%.

In both models, the contractor factor (PRIME) is statistically significant but contributes less than 5 percent to explaining model variance. A nominal logistic regression was performed of the top 5 contractors (PRIME) versus functional objectives (cycle time, unit costs, procurement quantities) and research and development and procurement budgets. The coefficients and odds ratios are provided in Table XIII.

Table XIII. Nominal logistic regression coefficients and odds ratios

	Coefficients				Odds Ratios			
Predictor	**LMT/BA**	**NGC/BA**	**LMT/BA**	**GD/BA**	**LMT/BA**	**NGC/BA**	**LMT/BA**	**GD/BA**
Constant	-9.42	1.11	-11.90	-7.41				
Cycle.Mo	0.04	0.03	0.02	0.02	1.04	1.03	1.02	1.02
LN.RD.M	-2.37	-2.84	-2.34	-4.39	0.09	0.06	0.10	0.01
LN.P.M	-7.44	-4.62	-6.80	-7.12	0	0.01	0	0
LN.UC.M	9.32	6.71	9.60	11.24	11160.13	816.6	14782.46	75894.39
LN.P_no	9.52	5.73	9.33	10.56	13638.31	308.47	11266.67	38691.84

Of note, cycle time coefficients are two orders of magnitude smaller than other factor coefficients, meaning that cycle time is not a significant factor between contractors. The resource and objective factors have opposite signs. Odds ratios show a similar distinction, with cycle time odds ratios near 1 for all contractors.

Contractor response to cycle times relative to Boeing are significant (p-values less than 0.05 for 3 of four comparatives), but small in terms of coefficients and odds ratios. A one-way ANOVA test of cycle time by top 5 contractors showed a statistically significant difference between contractor mean cycle times[71] (Welch's test, F-value 6.31, p-value 0.000). A univariate analysis of variance of cycle time with the top 5 contractors (PRIME) and the products they deliver (Type)[72] shows that variances across groups are not equal. *This is due to the market segmentation of products across the top 5 contractors,* as shown in Figure 12 above. The contractors do not produce the same products for the DoD, resulting in different mean cycle times for different prime-product groups. These results imply that the top 5 DoD contractors:

- have different responses to resources and functional objectives, and thus different acquisition strategies between themselves,
- respond in the same way to resources (LN.RD.M, LN.P.M), and
- respond in the same way to functional objectives directly related to product delivery, specifically unit cost and procurement quantities (LN.UC.M, LN.P_no).

Differences in cycle times between prime contractors are significant to model classification because of market segmentation of products across contractors. Program offices may structure programs and contracts setting conditions for the prime contractors achieving cycle time objectives. Example approaches include structuring programs to deliver incremental capabilities and creating competition within specific product service codes.

Factor associations with cycle time quartiles

The dataset cycle times were divided into four quartiles (Q)[73] to test categorical factor associations to MDAP cycle time historical performance. Chi-square association tests were performed using equation (1)[74] categorical predictors against cycle time quartiles, on both the full dataset and two data subsets. The Chi-square test results for the full dataset are shown in Table XIV.

[71] Games-Howell test showed that General Dynamics is statistically different than Lockheed Martin (T-value 3.43, p-value 0.011), Northrop Grumman (T-value 4.24, p-value 0.001), and Raytheon (T-value 3.17, p-value 0.032).

[72] The SPSS univariate ANOVA includes an interaction term PRIME*Type. Levene's test of equality of error variances base on cycle time means: Levene statistic: 2.971, df1: 14, df2: 100, significance: 0.000.

[73] The median cycle times by quartile: 1st - 71, 2nd - 98, 3rd - 138, and the 4th quartile - 165 months.

[74] The trained linear regression model.

Table XIV. Quartiles vs. regression factors – full dataset

Factor		Q1	Q2	Q3	Q4	p-value[75]
SW.Gp	0	17	15	20	26	0.001
	1	21	23	20	7	
	2	5	0	2	6	
Joint	0	32	29	34	34	0.475
	1	11	9	8	5	
DEPEND	0	28	12	14	7	0.000
	1	15	26	28	32	
Reuse	0	12	19	13	15	0.176
	1	31	19	29	24	
COML	0	21	21	31	35	0.000
	1	22	17	11	4	
Fin_Uns	0	27	15	15	6	0.000
	1	16	23	27	33	
Xx	under-represented in quartile					
Xx	over-represented in quartile					
p-value is for likelihood ratio						

Two factors (Joint and Reuse) did not show an association between the factors and cycle time quartiles. Three (DEPEND, COML, and Fin_Uns) were under- and over-represented in the 2nd and 4th quartiles. Waterfall-type software development processes (SW.Gp = 0) are over-represented in the 4th quartile, while agile, incremental or other types are over-represented in the 1st and 2nd quartiles.

The Chi-square association results by quartile when the GAO assessed neither system technology or system design as mature (dataset group 00) are in Table XV.

Table XV. Cycle time quartiles by regression factors – 00 dataset

Factor	#	1	2	3	4	p-value
SW.Gp	0	3	7	6	16	*
	1	7	9	9	0	
	2	3	0	0	1	
Joint	0	9	9	10	17	0.004
	1	4	7	5	0	
DEPEND	0	8	2	4	3	0.023
	1	5	14	11	14	
Reuse	0	1	14	6	1	0.000
	1	12	2	9	16	
COML	0	5	6	12	16	0.000
	1	8	10	3	1	
Fin_Uns	0	9	6	8	5	0.132
	1	4	10	7	12	

[75] A p-value less than 0.05 is evidence to reject factor independence and conclude the quartiles and categorical factor are associated.

Chi-square results were not calculated for SW.Gp, as 2 cells had expected counts less than 1. Existing technology reuse (Reuse = 1) is over-represented in the 1st and 4th quartiles suggesting the importance of selecting technologies appropriate for the intended use.

The second subset is when the GAO assessed *both* the system technology and system design as mature (dataset group 11). The results are shown in Table XVI.

Table XVI. Cycle time quartiles by regression factors – 11 dataset

Factor		Q1	Q2	Q3	Q4	p-value
SW.Gp	0	8	2	11	8	
	1	3	9	10	6	0.112
	2	2	0	2	2	
Joint	0	11	11	21	13	0.289
	1	2	0	2	3	
DEPEND	0	9	4	10	3	0.046
	1	4	7	13	13	
Reuse	0	3	2	5	12	0.002
	1	10	9	18	4	
COML	0	9	8	15	13	0.734
	1	4	3	8	3	
Fin_Uns	0	10	4	7	0	0.000
	1	3	7	16	16	

Three factors – Joint designation (Joint), software development type (SW.Gp) and use of commercial technology (COML) were not associated with cycle time quartiles. Technology reuse (Reuse) and financial instability (Fin_Uns) are associated with cycle time quartiles, with Reuse (Reuse =0) over-represented in the 4th quartile and Fin_Uns over-represented in the 1st (Fin_Uns=0) and 4th (Fin_Uns=1) quartiles.

Cycle time and change in cycle time correlations against GAO continuous predictors were tested by quartile using Spearman's rho and are summarized in Table XVII.

Table XVII. Spearman's correlation results by cycle time quartiles

	Cycle time, months (Cycle.Mo)				Percent change in cycle time (Cy.Mo.PCT)				
	Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4
RD.M	0.56	*	0.38	0.49	RD.M	**-0.38**	0.37	*	0.41
RD.M.PCT	**-0.30**	0.31	0.33	0.32	RD.M.PCT	0.32	0.49	0.29	0.48
P.M	*	*	0.31	*	P.M	*	*	*	*
P.M.PCT	**-0.27**	*	0.26	*	P.M.PCT	0.27	*	*	*
UC.M	*	*	*	*	UC.M	**-0.38**	*	*	*
UC.M.PCT	*	*	*	0.41	UC.M.PCT	*	0.36	0.06	0.33
P_no	*	*	*	*	P_no	0.36	*	**-0.37**	*
P_no.PCT	*	*	*	*	P_no.PCT	*	*	*	*

p-value <0.1 (shaded) *p-value > 0.1

p-value <0.05 (shaded) **Bold < 0**

These correlations were performed by testing predictors against cycle times (or percent change in cycle times) in each quartile for the full dataset. These results show significant weak-to-moderate correlations between these predictors and cycle times and percent change in cycle times within each quartile. These results also show the positive relationship between research and development budgets and cycle times[76]. Change in unit cost (UC.M) and procurement quantity change (P_no.PCT) were significant random forest predictors but are not correlated with cycle time by quartile. A test of correlations over the full dataset shows UC.M.PCT is significant for both (Cycle.Mo: $\rho = 0.406$, $p = 0.010$; Cy.Mo.PCT: $\rho = 0.325$, $p=0.043$).

[76] Expressed as LN.RD.M in equation (1).

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Conclusions, Relevance and Future Work

Conclusions

The pace of technology and adversary change continues to push the DoD for faster product delivery. The research showed that program cycle time may be predicted from programmatic resources and acquisition strategy decisions (research hypothesis 1), and that percent change in program cycle time may be predicted from programmatic structural changes (research hypothesis 2). Significant cycle time predictors included the size of research and development budgets, the planned use of appropriate commercial technology, appropriate reuse of existing technology, avoiding dependency on other programs, and avoiding financial instability. Significant cycle time predictors changed with system maturation. Major schedule change predictors included the percent change in procurement budgets, the number of critical technology elements the program requires to achieve performance, the DoD acquisition model used, and program financial instability.

Acquisition strategies were classified based on functional objectives of cycle times, unit cost, and procurement quantities. Unit cost and procurement quantities were shown to be strongly related. Cycle times were shown to be affected by resources, initial acquisition strategy decisions, and program maturation.

Acquisition process streamlining to reduce cycle times showed the importance of initial programmatic decisions, such as use of commercial technology or reuse of existing technology. Most streamlining occurred during program development; approximately 1/3 of programs in this research intentionally modified processes either during program development or in execution. These process changes were not shown to reduce overall cycle time growth between 2007 – 2018, but managed to control process cost growth.

When program technologies are immature, programs should consider using commercial technology and focusing on low unit costs. A decision framework was proposed to help program offices and acquisition executives identify example programs and approaches to lowering program cycle times.

The top 5 defense contractors were shown to have responses within the defense-unique product market. The research showed that the government can create competitive service markets *regardless of* competitive or non-competitive contract awards. Mean cycle times were shown to differ between such markets. Innovation (as measured by research and development budgets) did affect program cycle time. The top 5 contractors have statistically different outcomes in terms of programmatic resources and functional objectives, and likely differing acquisition strategies. The top 5 contractors respond in the same way to resources, unit costs, and procurement quantities. Cycle times across prime contractors are different due to market segmentation.

Relevance and contribution to the practice

This research provided quantitative insight into acquisition strategy factors affecting program cycle times and cycle time growth. Significant associations with faster cycle times were identified for key predictors. The research identified relationships between market factors and program cycle times, and relationships of cycle times to other program functional objectives.

The research identified risks related to unexpected factor interactions and dependencies during planning and execution, and provided a structured decision framework to help program offices identify approaches to changing cycle time functional objectives in execution. The research identified the significance of acquisition strategy choices made during program development ("structural choices") to cycle time outcomes. Similarly, streamlining and tailoring were used mainly during program development. A structured decision framework was presented to help program offices find example programs to assess for prior successful responses when faced with changing functional objectives such as lowering cycle times.

All research objectives were achieved. Several research datasets from publicly released data were created and are available to other researchers upon request. Quantitative methods identified specific predictors within the datasets affecting program cycle times and cycle time change.

There were three significant contributions to the practice: identifying acquisition strategy choices during program development affecting program cycle time outcomes, developing a framework assisting with in-execution responses, and the analysis of the top 5 contractor functional outcomes in the DoD-unique market supporting cycle time incentive strategies.

Future Work

Future research should include reperforming this research on a larger government-controlled dataset and developing quantitative risk factors associated with significant factor interactions and dependencies. The market analysis provided support for the government creating and managing market competition and innovation at the product and service code level. The FPDS dataset are large, and require curation, but do contain significant useful information related to competition and awards. Additional research is recommended to develop quantitative defense market factors from a contractor perspective. Finally, the streamlining analysis should be performed for selected programs using internal program documentation, and findings compared with open source results.

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Appendix

Variable	Description	Source	Notes	Type
ACQ_P	acquisition plan model factor	calculated	based on DoD Instruction 5000.02	categorical
act.IOC	actual IOC date (or latest estimate)	calculated	GAO or SAR report	date
AO	Contract action obligations ($)	FPDS	FPDS.gov	continuous
B.C	interval between milestones B and C, months	calculated	GAO or SAR report	continuous
C3I	problem with communications, control, command, intel during OT (1=yes)	calculated	GAO or DOTE report	binary
CA	Contract action (count)	FPDS	FPDS.gov	continuous
CC.Sked	cost change attributed to schedule, base year $M	SAR	SAR Summary report	continuous
CC.Sked_1	cost change attributed to schedule, Then year $M	SAR	SAR Summary report	continuous
COML	Program depends on commercial technologies (1=yes)	calculated	GAO or SAR report	binary
complex_sys	system is complex	calculated	GAO or SAR report	binary
CONTROL	problem with system control during OT (1=yes)	calculated	GAO or DOTE report	binary
CTC.Gp	contract type (cost/fixed price, incentive or fixed fee)	calculated	GAO or SAR report	categorical
CTC_TY	Contract type factor	calculated	GAO or SAR report	categorical
CTES	Count of program continuous variables	GAO	GAO or SAR report	continuous
Cy.Mo.PCT	percent change in cycle time since program start	GAO	0% if reported as NA by GAO	continuous
Cy.Mo1	actual cycle time	calculated	GAO, SAR report, or published notice	continuous
Cycle.Mo	cycle time in months	GAO	calculated if reported as NA by GAO	continuous
DEPEND	Program depends on other programs (1=yes)	calculated	GAO or SAR report	binary
Design.m	Program assessed by GAO as achieving KP2 (Design maturity) (1=yes)	GAO	GAO or DOTE report	binary
Dev_Ty	Dev development approach factor (single step/incremental) (incremental=1)	calculated	GAO or SAR report	binary
EARNINGS.M	Reported annual Net Earnings ($M)	10-K	Or net income	continuous
Eng	cost change attributed to Engineering changes, base year $M	SAR	SAR Summary report	continuous
Eng_1	cost change attributed to Engineering changes, Then year $M	SAR	SAR Summary report	continuous
EVENT	Nearest reported program event	calculated	GAO or SAR report	categorical
EVENT_dt	EVENT date (YYYY-MM)	calculated	GAO or SAR report	date
Fast	Program is intended to be rapid (1=yes)	calculated	GAO or SAR report	binary

Fast2.C	Program clustered as Fast (4 groups) (not used)	calculated	calculated	categorical

Variable	Description	Source	Notes	Type
Fin_Uns	> 10% change in funding (since program start)	calculated	GAO or SAR report	binary
Fixedprice	contract is fixed price (1=yes)	calculated	GAO or SAR report	binary
GAO.yr	year of GAO report reference	GAO		continuous
incentive	contract is incentive (1=yes)	calculated	GAO or SAR report	binary
INTEG	problem with system integration during OT (1=yes)	calculated	GAO or DOTE report	binary
INTEROP	problem with interoperability during OT (1=yes)	calculated	GAO or DOTE report	binary
IOC	Initial Operational Capability date (YYYY-MM)	calculated	GAO or SAR report	date
IOC.T	observation is past IOC (1= yes)	calculated	GAO or SAR report	binary
Joint	Joint categorical factor (1=yes)	calculated	GAO or SAR report	binary
LN.P.M	natural log transform of P.M	calculated	LN(P.M+1)	continuous
LN.P_no	natural log transform of P_no	calculated	LN(P_no _+1)	continuous
LN.RD.M	natural log transform of RD.M	calculated	LN(RD.M+1)	continuous
LN.UC.M	natural log transform of UC.M	calculated	LN(UC.M+1)	continuous
Maturity	Product is mature (1=yes)	calculated	GAO or SAR report	binary
MDAP	Program short title	GAO	acronym	categorical
MS_B	Program Milestone B date (YYYY-MM)	calculated	GAO or SAR report	date
MS_C	Program Milestone date (YYYY-MM)	calculated	GAO or SAR report	date
NM	Program incurs a Nunn-McCurdy Breach (1=yes)	calculated	GAO or SAR report	binary
OPER	problem with operator interfaces/operability during OT (1=yes)	calculated	GAO or DOTE report	binary
OT.time	duration of Operational testing (not used)	calculated	GAO or SAR report	continuous
P.M	procurement funding, $M	GAO		continuous
P.M.PCT	percent change in procurement funding since program start	GAO		continuous
P_no	procurement quantity objective	GAO		continuous
P_no.PCT	percent change in procurement quantity since program start	GAO	0% if reported as NA by GAO	continuous
PGM.Gp	Program group (Single step/incremental development & production)	calculated	GAO or SAR report	categorical
PM.oth	External influences on PMO (1=yes)	calculated	GAO or SAR report	binary
PRIME	Prime contractor short title factor	various	e.g., BA, GD, LMT, NOC(NGC), RTN	categorical
PRIME1	Prime contractor designator 1-5	calculated	1=BA, 2=GD, 3=LMT, 4=NGC, 5=RTN	categorical

Prod_m	Program assessed by GAO as achieving KP3 (Production maturity) (1=yes)	GAO	GAO or DOTE report	binary

Variable	Description	Source	Notes	Type
Prod_Ty	Production approach factor (single step/incremental) (incremental=1)	calculated	GAO or SAR report	binary
PROFIT.PCT	Percent profit	Calculated	EARNINGS.M/ REVENUE.M	continuous
PROP.PW.EN	problem with Propulsion, power, energy sub-systems during OT (1=yes)	calculated	GAO or DOTE report	binary
Prototype	Program uses prototypes (1=yes)	calculated	GAO or SAR report	binary
PSC Code	PSC Code from contract	FPDS		categorical
PSC Type	Product and Service Code	FPDS	P= product S= Service	categorical
Q	Cycle time quartile	calculated	calculated	categorical
Q1	Cycle time is in first quartile (1=yes)	calculated	calculated	binary
Q2	cycle time is in 2nd quartile (1=yes)	calculated	calculated	binary
Q3	cycle time is in 3rd quartile (1=yes)	calculated	calculated	binary
Q4	cycle time is in 4th quartile (1=yes)	calculated	calculated	binary
RD.INTENSITY	MDAP research intensity	calculated	RD.M/(RD.M+P.M)	continuous
RD.M	research and development (R&D) funding, $M	GAO		continuous
RD.M.PCT	percent change in R&D funding since program start	GAO		continuous
ref	pdf page number for GAO report	GAO		index
Req_Uns	Change in requirements (1=yes)	calculated	GAO or SAR report	binary
Restr	Program restructured (1=yes)	calculated	GAO or SAR report	binary
Reuse	Program reuses military technologies/systems (1=yes)	calculated	GAO or SAR report	binary
REVENUE.M	Reported annual Revenue ($M)	10-K	Or Sales	continuous
RMA	problem with reliability / availability during OT (1=yes)	calculated	GAO or DOTE report	binary
SEN.W	problem with sensors or weapons payloads during OT (1=yes)	calculated	GAO or DOTE report	binary
SoS_part	intended as part of a system of systems	calculated	GAO or SAR report	binary
Start_dt	Program start date (YYYY-MM)	calculated	GAO or SAR report	date
STRUCT	problem with Structures during OT (1=yes)	calculated	GAO or DOTE report	binary
SVC	short title for service (Army, Navy, Air Force, DoD)	GAO		categorical
SVC_1	integer factor (Army=1, Navy=2, Air Force=3, DoD=4)	calculated		categorical
SW	problem with Software during OT (1=yes)	calculated	GAO or DOTE report	binary

Variable	Description	Source	Notes	Type
SW.Gp	SW development model (Waterfall, incremental, other)	calculated	GAO or SAR report	categorical
SW_APP	SW development approach factor	calculated	GAO or SAR report	categorical
SWAP	problem with SWAP (size, weight, power) during OT (1=yes)	calculated	GAO or DOTE report	binary
Tech_m	Program assessed by GAO as achieving KP1 (Tech maturity) (1=yes)	GAO	GAO or DOTE report	binary
traditional	Program is not tailored (1=yes)	calculated	GAO or SAR report	binary
TRLe	Estimated Technology readiness level	calculated	GAO or DOTE report	categorical
Type	Commodity type (AIR, SHIP, GND, MSL, SPACE, C3I)	calculated	GAO or SAR report	categorical
Type_1	integer type factor (AIR=1, SHIP=5, GND=3, MSL&SPACE=4, C3I=2)	calculated	GAO or SAR report	categorical
UC.M	unit cost, $M	GAO		continuous
UC.M.PCT	percent change in unit cost since program start	GAO	0% if reported as NA by GAO	continuous
X	dataset row number	index		index

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