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OPTIMIZATION OF AMMUNITION PREPARATION STRATEGIES FOR MODERN ARTILLERY OPERATIONS IN COMPUTER SIMULATION

The experience of modern warfare, particularly from public reports on the Russia-Ukraine conflict, highlights significant changes in military strategies, tactics, and technology.

The heavy reliance on artillery and the high demand for shells pose major logistical, storage, and strategic challenges. Poor-quality ammunition can reduce combat effectiveness, damage equipment, jeopardize operations, and put personnel at risk, creating a cascade of additional problems.

The study was aimed at studying the effectiveness and optimization of the additional quality control strategy for ammunition. The focus was on acceptance sampling algorithms to maintain high productivity while optimizing inspection efficiency. The impracticality of 100 % inspection was taken into account.

The study develops and implements specialized acceptance sampling plans adapted to the unique quality and operational requirements of each type of artillery mission. Using iterative calculations, optimal sample sizes and acceptance criteria are established to meet predefined quality levels, minimizing resource consumption and inspection time. The developed sampling plans are structured to find balance between the allowed number of defects and inspection efficiency, ensuring that high-quality ammunition is allocated for destructive fire missions, while properly inspected but larger batches of ammunition are allocated for suppressive fire combat missions.

The new quality control step could be added to the game scenarios of ARMA 3, or to any other warfare simulations, and show that the acceptance plan strategy effectively reduces costs, increases operational safety and ensures readiness for artillery missions. The proposed statistical methods provide a reliable and adaptable approach for integrating quality control into the preparation of artillery ammunition, ensuring reliable supply in difficult combat conditions.

Keywords: *computer simulations, artillery operations, stochastic models, quality control, acceptance sampling.*

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1. Introduction

The experience of modern warfare, particularly insights gained from numerous public reports on the Russia-Ukraine conflict, highlights a significant evolution in military strategies, combat tactics, and warfare technologies. This conflict has demonstrated the increasing role of drone warfare, electronic warfare, precision-guided munitions, and real-time intelligence in shaping battlefield outcomes. However, along with these advancements, new challenges have emerged, including logistical vulnerabilities, the rapid depletion of ammunition stockpiles, and the growing importance of securing supply chains against disruption [1].

One of the unusual characteristics of the Russia-Ukraine conflict is the fact the artillery systems, and ammunition components are received from many different manufacturers from all over the world.

The importance of artillery and huge demand on artillery shells creates many additional problems with logistics, storage and strategy decisions. Due to high demand, manufacturers are trying to speed up production and because of this, quality is greatly decreased.

Low quality of ammunition, for example, a deviation of projectile weight from the standard, or a quality of propelling charge, could affect shooting accuracy, damage artillery equipment, or increased time for task completion, and in modern artillery combat every additional minute of shooting could greatly increase chances for opponent retaliation and endanger the entire operation and the lives of personnel.

All these challenges confirm the necessity of an additional validation process for all ammunition parts received from a manufacturer, at the step of preparation to combat mission, before the artillery goes into position. Because, usually, such preparation takes place in hidden places and relatively close to the frontline, it is almost impossible to apply thorough checks, with the lack of additional personnel and time for it.

In a reality of modern warfare, it is very important to minimize the time needed for each preparation and additional validation step without the need to use expensive equipment.

One of the critical tools employed in quality control, which doesn't require any additional tools, is acceptance sampling, a statistical method used to determine whether a batch of products meets the desired quality criteria without inspecting every single item [2], which it is further possible to optimize for each type of combat mission.

The application of statistical methods in acceptance sampling is governed by probability theory and statistical inference. Key distributions, such as the binomial, hypergeometric, and Poisson distributions, play a crucial role in defining the acceptance criteria.

Proposed strategies for ammunition quality control procedure could be implemented in any type of computer simulation. As an example, for our implementation let's use military simulation ARMA 3. The game engine of ARMA 3 allows easily insert additional validation step in the gameplay flow and let users to test new strategies.

The aim of this research is to research and find optimal quality control strategy for ammunition preparation for different types of military operations to ensure mission success and save expensive resources.

2. Materials and Methods

2.1. Goals

It is necessary to address the critical challenge of quality control for artillery ammunition to ensure reliability and effectiveness in combat operations and find an optimal strategy for the ammunition preparation step before every artillery mission. For a mission to be successfully executed, a predetermined quantity of ammunition must be prepared of the required quality to meet operational demands [3, 4]. As an example, for our calculations, let's consider projectile M107, which is used by some artillery systems in the ARMA 3. For our model it is possible to assume that each artillery shell is composed of two primary components: the cartridge case, which houses the propellant, and the bursting charge, which delivers the explosive impact [5, 6]. Each of these parts could be received from the factory separately and assembled at the stage of preparation to a combat operation. Our model and methods could be easily scaled for more complex shell structure and all types of artillery systems.

To maintain high-quality standards, it is necessary to conduct a thorough inspection of each component upon receiving a new batch of ammunition. This involves verifying the structural integrity, material consistency, and adherence to design specifications of both the cartridge case and the bursting charge. By implementing stringent quality control measures at both the component and assembly stages, it is possible to minimize defects, enhance operational safety, and guarantee the effectiveness of artillery rounds in the field.

Due to the specifics of military operations, it is rarely possible to examine every shell, so it is necessary to use a more optimal way of checking ammunition quality.

ARMA 3 have many different game scenarios, with the different task for the artillery units: overwatch, harass, blind, suppress, neutralize, destroy, interdict and direct fire [7]. Model could be applied for all of the, but for our research let's consider two essentially "opposite" types of tasks:

– *Suppressive Fire*: The goal of suppression is to neutralize the enemy's ability to retaliate, preventing them from effectively deploying their weapons, maneuvering, or observing the battlefield. This is best achieved by using medium to high-density fire, continuously applying pressure on enemy positions to disrupt their actions and force them into defensive postures. Suppressive fire is often used to support advancing friendly forces or to control key strategic areas by denying the enemy freedom of movement.

– *Destructive Fire*: Unlike suppression, which aims to disrupt enemy actions, destruction focuses on eliminating enemy assets entirely. The objective is to inflict maximum damage in the shortest possible time, ensuring that enemy forces, weapon systems, or fortified positions are rendered permanently inoperative. This requires a high volume of rounds, delivered with precision, targeting critical infrastructure, command posts, or high-value enemy units. Destructive fire is often employed in preemptive strikes or counter-battery operations to neutralize threats before they can engage friendly forces.

2.2. Methodology

Each type of artillery operation imposes distinct requirements on ammunition quality to ensure mission effectiveness. The level of precision, reliability, and consistency of ammunition directly influences the success of the operation, whether it is aimed at suppression or destruction.

For destructive fire missions, the primary objectives are speed, accuracy, and maximum impact. Given that these operations require rapid elimination of enemy assets, ammunition must be manufactured and inspected to the highest quality standards. ARMA 3 game engine Factors such as propellant consistency, shell stability, and detonation reliability play a crucial role in ensuring that each round reaches its intended target with minimal deviation. A malfunctioning shell, misfire, or inaccurate round can lead to mission failure, wasted resources, and potential collateral damage [5, 8]. Therefore, destructive fire demands ammunition with strict quality control, precise assembly, and rigorous testing to guarantee high effectiveness under combat conditions.

On the other hand, suppressive fire missions prioritize sustained firepower over pinpoint accuracy. The goal of suppression is to disrupt enemy operations, restrict movement, and create a psychological and tactical advantage rather than immediately eliminating enemy forces. Since this type of mission relies on continuous fire over a larger area, the quality requirements for ammunition are somewhat more flexible.

While the ammunition must still be reliable and function properly, minor deviations in accuracy or slight variations in explosive performance are more tolerable compared to destructive fire missions [9]. This allows for a wider acceptance range in quality control, enabling the use of ammunition that might not meet the highest precision standards but is still effective for its intended role.

To address the challenge of ensuring the reliability and consistency of ammunition preparation for artillery operations in the simulation, it is possible to implement statistical methods of quality control, including process control techniques, defect analysis, and performance monitoring. Additionally, let's apply acceptance sampling methods to systematically inspect and evaluate batches of ammunition, determining whether they meet predefined quality standards before deployment in the field [7, 10, 11].

Acceptance sampling procedures serve as quality control measures, designed against potential declines in product quality. Their primary function is to detect and reject substandard batches before they reach deployment. However, these procedures should be viewed as temporary safeguards rather than long-term solutions.

The primary reasons to use acceptance sampling [2, 10]:

Unstable or Unpredictable Production Processes. When a manufacturing process is not under control, its output becomes erratic and unpredictable. In such cases, random sampling is necessary to evaluate product quality after production, as process fluctuations make real-time monitoring ineffective.

Balancing Inspection Efficiency and Risk Management. 100 % inspection is inefficient, with studies estimating that even full-scale screening detects only around 80 % of defects. At the same time, eliminating inspection entirely (0 % sampling) introduces significant risk. Acceptance sampling provides a practical middle ground, ensuring that defective batches are identified and rejected without excessive resource consumption.

Preventing Deliberate Submission of Defective Material. In real-world manufacturing, production pressures or profit-driven decisions may lead to intentional submission of defective materials. Acceptance sampling acts as a safeguard against fraud, ensuring that compromised products are detected before reaching end-users.

Cost and Practicality Considerations. Implementing real-time process control can be cost-prohibitive or require specialized personnel, making it impractical in certain settings. Acceptance sampling offers a cost-effective, straightforward alternative that ensures product evaluation without the need for complex process monitoring systems, which is especially important in the military environment.

3. Results and Discussions

3.1. Sampling plan

The sampling plan is n and c, where n is the sample size and c represent the acceptance number or maximum number of defectives allowed in the sample for acceptance of the lot.

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Effective use of sampling procedures requires a thorough understanding and precise definition of the characteristics of the sampling plans being implemented. A key consideration is the balance between producer and consumer risk.

To define the operating characteristic (OC) curve, two critical points are typically specified: producer risk (α) and consumer risk (β). The producer's risk (α) represents the probability of rejecting a lot that meets an acceptable quality level (AQL), while the consumer's risk (β) reflects the probability of accepting a lot with an unsatisfactory quality level (Fig. 1). In practice, quality levels p_1 or better should be accepted the majority of the time, whereas quality levels p_2 or worse should be rejected in most cases.

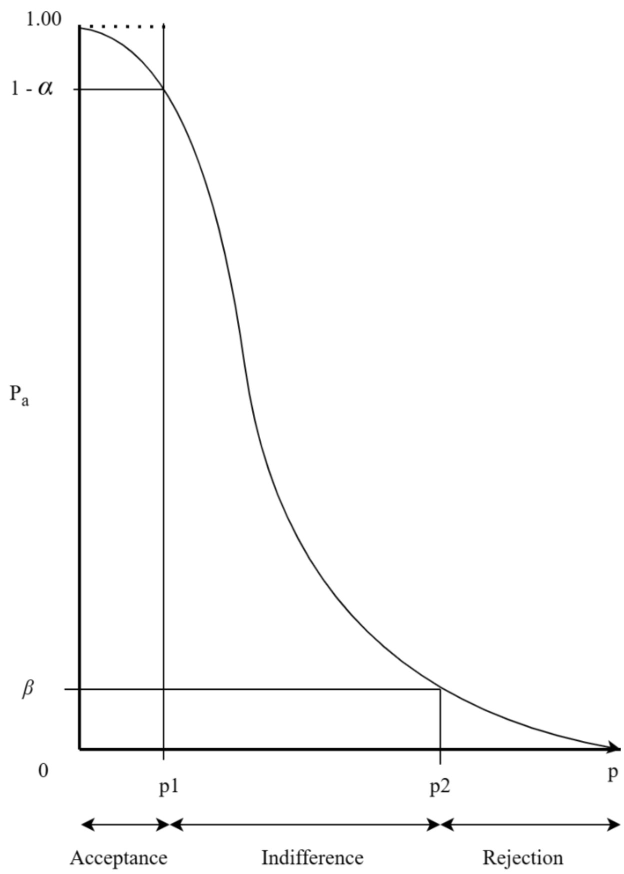

Fig. 1. Relations of p_1, p_2, α, β to the OC curve

In some cases, only a single set of parameters is specified. When this occurs, any sampling plan with an OC curve passing through the designated points is considered acceptable, as it satisfies the required quality assurance criteria.

3.2. Binomial Distribution

Binomial distribution is undoubtedly the most widely utilized in acceptance sampling. It serves as a complement to the hypergeometric distribution, as it is applied when sampling an attribute characteristic from an infinite lot or ongoing process. Additionally, it is used when sampling from a finite lot with replacement, making it a fundamental tool for estimating defect probabilities and evaluating quality control decisions.

Its frequency function is:

$$f(x) = C_x^n p^x (1-p)^{n-x}, \quad (1)$$

where n – sample size; p – proportion defective; q – proportion effective; x – number of occurrences.

Artillery shell is assembled from 2 parts – the cartridge case and the bursting charge. Let's assume that Artillery shells are defective if only both cartridge and charge parts are defective [6].

It is necessary to create an Acceptance Plan for products the shells and each part.

For artillery shells it is necessary to guarantee the defect rate <= 5 % with 90 % confidence.

Let's calculate the maximum allowed defective percentage for each part based on the condition that artillery shell (product C) is defective only if both parts used in its assembly are defective.

Let's define the defective rate for the cartridge case (product A) and bursting charge (product B) as p_a and p_b, respectively.

Let's assume that defects between each part are independent.

The probability that product C is defective is the probability that both A and B are defective:

$$p(Cdef) = P(Adef \cap Bdef) = pA \cdot pB. \quad (2)$$

To simplify, assume $p_a = p_b = p$ (equal defect rates for A and B). Then:

$$p \le 0.05 \approx 0.2236.$$

For groups A (cases) and B(charges) it is necessary to create an Acceptance Plan that will reject lots with $p \ge 0.2$, with the 90 % confidence.

And for group C (shells) it is necessary to create an Acceptance Plan that will reject lots with $p \ge 0.05$, with 90 % confidence.

Using the iterative method it is possible to find optimal sample size (n) and acceptable defective product limit (c) in sample size.

It is possible to use binomial distribution formula:

$$L(p) = \sum_{k=0}^{c} C_k^n p^k (1-p)^{n-k}. \quad (3)$$

It is necessary to find a sampling plan which will satisfy two conditions:

1) $L(p_1) \ge 0.95$; $p_1 = 0.01$, where p_1 – defective rate in a batch of cartridge cases and $L(p_1)$ – probability of accepting the sample size of cartridge cases.

Which means that with this sampling plan it is possible to *accept* a batch with a 1 % defect rate with 95 % confidence:

2) $L(p_2) \le 0.1$; $p_2 = 0.06$, where p_2 – defective rate in a batch of bursting charges and $L(p_2)$ – probability of accepting the sample size of bursting charges.

Which means that with this sampling plan it is possible to reject a batch with a 6 % defect rate with 90 % confidence.

Using iterative methods for $n = 100–115$; $c = 1–4$, it is possible to calculate values for different sampling plans and find the one that will fulfill both conditions (Table 1).

Analyzing the results it is possible to see that sampling plan $n = 110$, $c = 3$ fulfils both conditions for group C:

$$L(p_1) = 0.975; \ L(p_2) = 0.0980.$$

For groups A and B it is necessary a less strict sampling plan:

1) $L(p_1) \ge 0.95$; $p_1 = 0.1$, where p_1 – defective rate in a batch and $L(p_1)$ – probability of accepting the sample size.

Which means that with this sampling plan it is possible to accept a batch with a 10 % defect rate with 95 % confidence:

2) $L(p_2) \le 0.1$; $p_2 = 0.2$, which means that with this sampling plan it is possible to reject a batch with a 20 % defect rate with 90 % confidence.

Using iterative methods for $n = 30–45$; $c = 1–5$, it is possible to calculate values for different sampling plans and find the one that will fulfill both conditions (Table 2).

Table 1

Chances of accepting the lot with $p_1=0.01$ and $p_2=0.06$ for different sample sizes

n	$c=1$	$c=2$	$c=3$	$c=4$
$n=100$	$L(p_1)=0.7358$ $L(p_2)=0.0152$	$L(p_1)=0.9206$ $L(p_2)=0.0566$	$L(p_1)=0.9816$ $L(p_2)=0.1430$	$L(p_1)=0.9966$ $L(p_2)=0.2768$
$n=101$	$L(p_1)=0.7321$ $L(p_2)=0.0144$	$L(p_1)=0.9188$ $L(p_2)=0.0541$	$L(p_1)=0.9810$ $L(p_2)=0.1378$	$L(p_1)=0.9964$ $L(p_2)=0.2688$
$n=102$	$L(p_1)=0.7284$ $L(p_2)=0.0136$	$L(p_1)=0.9169$ $L(p_2)=0.0517$	$L(p_1)=0.9804$ $L(p_2)=0.1328$	$L(p_1)=0.9963$ $L(p_2)=0.2609$
$n=103$	$L(p_1)=0.7247$ $L(p_2)=0.0129$	$L(p_1)=0.9150$ $L(p_2)=0.0495$	$L(p_1)=0.9798$ $L(p_2)=0.1280$	$L(p_1)=0.9961$ $L(p_2)=0.2532$
$n=104$	$L(p_1)=0.7210$ $L(p_2)=0.0123$	$L(p_1)=0.9131$ $L(p_2)=0.0473$	$L(p_1)=0.9791$ $L(p_2)=0.1232$	$L(p_1)=0.9959$ $L(p_2)=0.2457$
$n=105$	$L(p_1)=0.7173$ $L(p_2)=0.0116$	$L(p_1)=0.9112$ $L(p_2)=0.0452$	$L(p_1)=0.9785$ $L(p_2)=0.1187$	$L(p_1)=0.9958$ $L(p_2)=0.2383$
$n=106$	$L(p_1)=0.7136$ $L(p_2)=0.0110$	$L(p_1)=0.9093$ $L(p_2)=0.0432$	$L(p_1)=0.9778$ $L(p_2)=0.1143$	$L(p_1)=0.9956$ $L(p_2)=0.2312$
$n=107$	$L(p_1)=0.7099$ $L(p_2)=0.0104$	$L(p_1)=0.9073$ $L(p_2)=0.0412$	$L(p_1)=0.9771$ $L(p_2)=0.1100$	$L(p_1)=0.9954$ $L(p_2)=0.2242$
$n=108$	$L(p_1)=0.7062$ $L(p_2)=0.0099$	$L(p_1)=0.9053$ $L(p_2)=0.0394$	$L(p_1)=0.9764$ $L(p_2)=0.1059$	$L(p_1)=0.9952$ $L(p_2)=0.2173$
$n=109$	$L(p_1)=0.7025$ $L(p_2)=0.0094$	$L(p_1)=0.9033$ $L(p_2)=0.0376$	$L(p_1)=0.9757$ $L(p_2)=0.1019$	$L(p_1)=0.9951$ $L(p_2)=0.2106$
$n=110$	$L(p_1)=0.6988$ $L(p_2)=0.0089$	$L(p_1)=0.9013$ $L(p_2)=0.0359$	$\mathbf{L(p_1)=0.9750}$ $\mathbf{L(p_2)=0.0980}$	$L(p_1)=0.9949$ $L(p_2)=0.2041$
$n=111$	$L(p_1)=0.6952$ $L(p_2)=0.0084$	$L(p_1)=0.8993$ $L(p_2)=0.0343$	$L(p_1)=0.9742$ $L(p_2)=0.0943$	$L(p_1)=0.9947$ $L(p_2)=0.1977$
$n=112$	$L(p_1)=0.6915$ $L(p_2)=0.0080$	$L(p_1)=0.8973$ $L(p_2)=0.0327$	$L(p_1)=0.9735$ $L(p_2)=0.0907$	$L(p_1)=0.9945$ $L(p_2)=0.1915$
$n=113$	$L(p_1)=0.6878$ $L(p_2)=0.0075$	$L(p_1)=0.8952$ $L(p_2)=0.0313$	$L(p_1)=0.9727$ $L(p_2)=0.0872$	$L(p_1)=0.9942$ $L(p_2)=0.1855$
$n=114$	$L(p_1)=0.6842$ $L(p_2)=0.0072$	$L(p_1)=0.8931$ $L(p_2)=0.0298$	$L(p_1)=0.9719$ $L(p_2)=0.0839$	$L(p_1)=0.9940$ $L(p_2)=0.1796$
$n=115$	$L(p_1)=0.6805$ $L(p_2)=0.0068$	$L(p_1)=0.8910$ $L(p_2)=0.0285$	$L(p_1)=0.9712$ $L(p_2)=0.0806$	$L(p_1)=0.9938$ $L(p_2)=0.1738$

Table 2

Chances of accepting the lot with $p_1=0.1$ and $p_2=0.2$ for different sample sizes

n	$c=1$	$c=2$	$c=3$	$c=4$	$c=5$
$n=30$	$L(p_1)=0.5535$ $L(p_2)=0.0105$	$L(p_1)=0.8122$ $L(p_2)=0.0442$	$L(p_1)=0.9392$ $L(p_2)=0.1227$	$L(p_1)=0.9844$ $L(p_2)=0.2552$	$L(p_1)=0.9967$ $L(p_2)=0.4275$
$n=31$	$L(p_1)=0.5366$ $L(p_2)=0.0087$	$L(p_1)=0.7992$ $L(p_2)=0.0374$	$L(p_1)=0.9329$ $L(p_2)=0.1070$	$L(p_1)=0.9821$ $L(p_2)=0.2287$	$L(p_1)=0.9961$ $L(p_2)=0.3931$
$n=32$	$L(p_1)=0.5200$ $L(p_2)=0.0071$	$L(p_1)=0.7861$ $L(p_2)=0.0317$	$L(p_1)=0.9262$ $L(p_2)=0.0931$	$L(p_1)=0.9796$ $L(p_2)=0.2044$	$L(p_1)=0.9954$ $L(p_2)=0.3602$
$n=33$	$L(p_1)=0.5036$ $L(p_2)=0.0059$	$L(p_1)=0.7728$ $L(p_2)=0.0268$	$L(p_1)=0.9192$ $L(p_2)=0.0808$	$L(p_1)=0.9770$ $L(p_2)=0.1821$	$L(p_1)=0.9946$ $L(p_2)=0.3290$
$n=34$	$L(p_1)=0.4877$ $L(p_2)=0.0048$	$L(p_1)=0.7593$ $L(p_2)=0.0226$	$L(p_1)=0.9119$ $L(p_2)=0.0700$	$L(p_1)=0.9741$ $L(p_2)=0.1619$	$L(p_1)=0.9937$ $L(p_2)=0.2996$
$n=35$	$L(p_1)=0.4720$ $L(p_2)=0.0040$	$L(p_1)=0.7458$ $L(p_2)=0.0190$	$L(p_1)=0.9042$ $L(p_2)=0.0605$	$L(p_1)=0.9710$ $L(p_2)=0.1435$	$L(p_1)=0.9927$ $L(p_2)=0.2721$
$n=36$	$L(p_1)=0.4567$ $L(p_2)=0.0032$	$L(p_1)=0.7321$ $L(p_2)=0.0160$	$L(p_1)=0.8963$ $L(p_2)=0.0522$	$L(p_1)=0.9676$ $L(p_2)=0.1269$	$L(p_1)=0.9917$ $L(p_2)=0.2464$
$n=37$	$L(p_1)=0.4418$ $L(p_2)=0.0027$	$L(p_1)=0.7183$ $L(p_2)=0.0135$	$L(p_1)=0.8881$ $L(p_2)=0.0450$	$L(p_1)=0.9641$ $L(p_2)=0.1120$	$L(p_1)=0.9905$ $L(p_2)=0.2225$
$n=38$	$L(p_1)=0.4272$ $L(p_2)=0.0022$	$L(p_1)=0.7045$ $L(p_2)=0.0113$	$L(p_1)=0.8796$ $L(p_2)=0.0387$	$\mathbf{L(p_1)=0.9603}$ $\mathbf{L(p_2)=0.0986}$	$L(p_1)=0.9891$ $L(p_2)=0.2004$
$n=39$	$L(p_1)=0.4129$ $L(p_2)=0.0018$	$L(p_1)=0.6906$ $L(p_2)=0.0095$	$L(p_1)=0.8709$ $L(p_2)=0.0332$	$L(p_1)=0.9562$ $L(p_2)=0.0866$	$L(p_1)=0.9877$ $L(p_2)=0.1800$
$n=40$	$L(p_1)=0.3991$ $L(p_2)=0.0015$	$L(p_1)=0.6767$ $L(p_2)=0.0079$	$L(p_1)=0.8619$ $L(p_2)=0.0285$	$L(p_1)=0.9520$ $L(p_2)=0.0759$	$L(p_1)=0.9861$ $L(p_2)=0.1613$
$n=41$	$L(p_1)=0.3855$ $L(p_2)=0.0012$	$L(p_1)=0.6629$ $L(p_2)=0.0066$	$L(p_1)=0.8526$ $L(p_2)=0.0244$	$L(p_1)=0.9475$ $L(p_2)=0.0664$	$L(p_1)=0.9844$ $L(p_2)=0.1442$
$n=42$	$L(p_1)=0.3724$ $L(p_2)=0.0010$	$L(p_1)=0.6490$ $L(p_2)=0.0056$	$L(p_1)=0.8431$ $L(p_2)=0.0208$	$L(p_1)=0.9427$ $L(p_2)=0.0580$	$L(p_1)=0.9826$ $L(p_2)=0.1287$
$n=43$	$L(p_1)=0.3595$ $L(p_2)=0.0008$	$L(p_1)=0.6352$ $L(p_2)=0.0046$	$L(p_1)=0.8334$ $L(p_2)=0.0178$	$L(p_1)=0.9377$ $L(p_2)=0.0506$	$L(p_1)=0.9806$ $L(p_2)=0.1145$
$n=44$	$L(p_1)=0.3471$ $L(p_1)=0.0007$	$L(p_1)=0.6214$ $L(p_2)=0.0039$	$L(p_1)=0.8235$ $L(p_2)=0.0151$	$L(p_1)=0.9325$ $L(p_2)=0.0440$	$L(p_1)=0.9784$ $L(p_2)=0.1018$
$n=45$	$L(p_1)=0.3350$ $L(p_2)=0.0005$	$L(p_1)=0.6077$ $L(p_2)=0.0032$	$L(p_1)=0.8134$ $L(p_2)=0.0129$	$L(p_1)=0.9271$ $L(p_2)=0.0382$	$L(p_1)=0.9761$ $L(p_2)=0.0902$

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Sampling plan $n=38$ and $c=4$ fulfil both conditions for group A and B:

$$L(p_1)=0.9603;\ L(p_2)=0.0986.$$

These acceptance plans allow to efficiently and in a small amount of time check the quality for a large amount of ammunition batches. Which is a good way to prepare ammunition for a "suppressing fire" type of missions.

No inspection process is always flawless. In fact, it is widely acknowledged that even a 100 % inspection does not guarantee the complete elimination of defective items, as human error, equipment limitations, and process inefficiencies can lead to overlooked defects.

Sample inspection is also prone to similar types of errors as full inspection. While one key advantage of sampling is the reduction in the number of items undergoing repetitive examination, factors such as human error, inspection fatigue, and subjective judgment can still lead to inaccuracies. These limitations may cause misclassification of defective items, ultimately resulting in an imprecise assessment of the overall quality of the batch being evaluated.

The following formula for the apparent level of quality p^* when the true incoming level defective is p:

$$p^* = p_1(1-p)+p(1-p_2), \qquad (4)$$

where p_1 – probability for a non-defective unit classified as a defective one; p_2 – probability for a defective unit classified as a non-defective one.

Let's assume that there is an inspection error due to the imperfections in inspection equipment:

$$p_1 = p_2 = 0.02.$$

To increase the efficiency of a sampling plan with an inspection error it is also necessary to decrease a confidence threshold for accepting a high-quality batch and rejecting a low-quality batch.

New conditions for the sampling plan for the artillery shells (product C), that include assembly error:

1) $L(p_1)\geq 0.85;\ p_1^*=0.02\cdot(1-0.01)+0.01\cdot(1-0.02)=$ $=0.0296;$

2) $L(p_2)\leq 0.15;\ p_2^*=0.02\cdot(1-0.06)+0.06\cdot(1-0.02)=$ $=0.0776.$

Using iterative methods for $n=85$–95; $c=2$–6, it is possible to calculate values for different sampling plans and find the one that will fulfill both conditions (Table 3).

Sampling plan $n=92$ and $c=4$ fulfils both conditions for group C:

$$L(p_1)=0.8624;\ L(p_2)=0.1499.$$

And for groups A and B there is a new sampling plan which takes into account inspection errors:

1) $L(p_1)\geq 0.85;\ p_1^*=0.02\cdot(1-0.1)+0.1\cdot(1-0.02)=$ $=0.116;$

2) $L(p_2)\leq 0.1;\ p_2^*=0.02\cdot(1-0.2)+0.2\cdot(1-0.02)=$ $=0.212.$

Using iterative methods for $n=70$–90; $c=10$–14, it is possible to calculate values for different sampling plans and find the one that will fulfill both conditions (Table 4).

Table 3

Chances of accepting the lot with an assembly error for $p_1^*=0.0296$, $p_2^*=0.0776$

n	$c=2$	$c=3$	$c=4$	$c=5$	$c=6$
$n=85$	$L(p_1)=0.5377$ $L(p_2)=0.0348$	$L(p_1)=0.7557$ $L(p_2)=0.0962$	$L(p_1)=0.8921$ $L(p_2)=0.2019$	$L(p_1)=0.9594$ $L(p_2)=0.3460$	$L(p_1)=0.9868$ $L(p_2)=0.5077$
$n=86$	$L(p_1)=0.5301$ $L(p_2)=0.0328$	$L(p_1)=0.7493$ $L(p_2)=0.0914$	$L(p_1)=0.8880$ $L(p_2)=0.1937$	$L(p_1)=0.9574$ $L(p_2)=0.3349$	$L(p_1)=0.9860$ $L(p_2)=0.4952$
$n=87$	$L(p_1)=0.5225$ $L(p_2)=0.0309$	$L(p_1)=0.7428$ $L(p_2)=0.0869$	$L(p_1)=0.8839$ $L(p_2)=0.1858$	$L(p_1)=0.9554$ $L(p_2)=0.3239$	$L(p_1)=0.9852$ $L(p_2)=0.4827$
$n=88$	$L(p_1)=0.5149$ $L(p_2)=0.0290$	$L(p_1)=0.7363$ $L(p_2)=0.0825$	$L(p_1)=0.8797$ $L(p_2)=0.1781$	$L(p_1)=0.9533$ $L(p_2)=0.3132$	$L(p_1)=0.9843$ $L(p_2)=0.4704$
$n=89$	$L(p_1)=0.5075$ $L(p_2)=0.0273$	$L(p_1)=0.7297$ $L(p_2)=0.0784$	$L(p_1)=0.8755$ $L(p_2)=0.1707$	$L(p_1)=0.9511$ $L(p_2)=0.3027$	$L(p_1)=0.9834$ $L(p_2)=0.4582$
$n=90$	$L(p_1)=0.5000$ $L(p_2)=0.0257$	$L(p_1)=0.7231$ $L(p_2)=0.0744$	$L(p_1)=0.8712$ $L(p_2)=0.1635$	$L(p_1)=0.9488$ $L(p_2)=0.2925$	$L(p_1)=0.9824$ $L(p_2)=0.4461$
$n=91$	$L(p_1)=0.4926$ $L(p_2)=0.0242$	$L(p_1)=0.7165$ $L(p_2)=0.0706$	$L(p_1)=0.8668$ $L(p_2)=0.1566$	$L(p_1)=0.9465$ $L(p_2)=0.2825$	$L(p_1)=0.9814$ $L(p_2)=0.4342$
$n=92$	$L(p_1)=0.4853$ $L(p_2)=0.0227$	$L(p_1)=0.7099$ $L(p_2)=0.0670$	**$L(p_1)=0.8624$** **$L(p_2)=0.1499$**	$L(p_1)=0.9442$ $L(p_2)=0.2727$	$L(p_1)=0.9804$ $L(p_2)=0.4224$
$n=93$	$L(p_1)=0.4780$ $L(p_2)=0.0214$	$L(p_1)=0.7033$ $L(p_2)=0.0636$	$L(p_1)=0.8578$ $L(p_2)=0.1435$	$L(p_1)=0.9418$ $L(p_2)=0.2632$	$L(p_1)=0.9793$ $L(p_2)=0.4108$
$n=94$	$L(p_1)=0.4708$ $L(p_2)=0.0201$	$L(p_1)=0.6966$ $L(p_2)=0.0603$	$L(p_1)=0.8533$ $L(p_2)=0.1373$	$L(p_1)=0.9393$ $L(p_2)=0.2539$	$L(p_1)=0.9782$ $L(p_2)=0.3994$
$n=95$	$L(p_1)=0.4637$ $L(p_2)=0.0189$	$L(p_1)=0.6899$ $L(p_2)=0.0572$	$L(p_1)=0.8486$ $L(p_2)=0.1313$	$L(p_1)=0.9367$ $L(p_2)=0.2448$	$L(p_1)=0.9770$ $L(p_2)=0.3881$

Table 4

Chances of accepting the lot with an assembly error for $p_1^*=0.116$, $p_2^*=0.212$

n	$c=10$	$c=11$	$c=12$	$c=13$	$c=14$
$n=70$	$L(p_1)=0.8160$ $L(p_2)=0.0984$	$L(p_1)=0.8928$ $L(p_2)=0.1645$	$L(p_1)=0.9423$ $L(p_2)=0.2519$	$L(p_1)=0.9712$ $L(p_2)=0.3567$	$L(p_1)=0.9867$ $L(p_2)=0.4716$
$n=71$	$L(p_1)=0.8036$ $L(p_2)=0.0889$	$L(p_1)=0.8839$ $L(p_2)=0.1505$	$L(p_1)=0.9365$ $L(p_2)=0.2333$	$L(p_1)=0.9679$ $L(p_2)=0.3345$	$L(p_1)=0.9849$ $L(p_2)=0.4473$
$n=72$	$L(p_1)=0.7908$ $L(p_2)=0.0801$	$L(p_1)=0.8745$ $L(p_2)=0.1374$	$L(p_1)=0.9304$ $L(p_2)=0.2158$	$L(p_1)=0.9642$ $L(p_2)=0.3131$	$L(p_1)=0.9829$ $L(p_2)=0.4234$
$n=73$	$L(p_1)=0.7777$ $L(p_2)=0.0721$	$L(p_1)=0.8648$ $L(p_2)=0.1253$	$L(p_1)=0.9239$ $L(p_2)=0.1991$	$L(p_1)=0.9603$ $L(p_2)=0.2924$	$L(p_1)=0.9808$ $L(p_2)=0.4000$
$n=74$	$L(p_1)=0.7642$ $L(p_2)=0.0648$	$L(p_1)=0.8547$ $L(p_2)=0.1140$	$L(p_1)=0.9171$ $L(p_2)=0.1835$	$L(p_1)=0.9561$ $L(p_2)=0.2727$	$L(p_1)=0.9784$ $L(p_2)=0.3772$
$n=75$	$L(p_1)=0.7505$ $L(p_2)=0.0581$	$L(p_1)=0.8442$ $L(p_2)=0.1036$	$L(p_1)=0.9098$ $L(p_2)=0.1687$	$L(p_1)=0.9516$ $L(p_2)=0.2537$	$L(p_1)=0.9758$ $L(p_2)=0.3550$
$n=76$	$L(p_1)=0.7364$ $L(p_2)=0.0521$	$L(p_1)=0.8333$ $L(p_2)=0.0939$	$L(p_1)=0.9022$ $L(p_2)=0.1549$	$L(p_1)=0.9467$ $L(p_2)=0.2357$	$L(p_1)=0.9730$ $L(p_2)=0.3336$
$n=77$	$L(p_1)=0.7222$ $L(p_2)=0.0466$	$L(p_1)=0.8221$ $L(p_2)=0.0850$	$L(p_1)=0.8942$ $L(p_2)=0.1420$	$L(p_1)=0.9416$ $L(p_2)=0.2186$	$L(p_1)=0.9700$ $L(p_2)=0.3128$
$n=78$	$L(p_1)=0.7076$ $L(p_2)=0.0416$	$L(p_1)=0.8105$ $L(p_2)=0.0769$	$L(p_1)=0.8859$ $L(p_2)=0.1299$	$L(p_1)=0.9361$ $L(p_2)=0.2024$	$L(p_1)=0.9667$ $L(p_2)=0.2928$
$n=79$	$L(p_1)=0.6929$ $L(p_2)=0.0371$	$L(p_1)=0.7986$ $L(p_2)=0.0694$	$L(p_1)=0.8771$ $L(p_2)=0.1187$	$L(p_1)=0.9303$ $L(p_2)=0.1870$	$L(p_1)=0.9631$ $L(p_2)=0.2737$
$n=80$	$L(p_1)=0.6781$ $L(p_2)=0.0330$	$L(p_1)=0.7863$ $L(p_2)=0.0625$	$L(p_1)=0.8680$ $L(p_2)=0.1082$	$L(p_1)=0.9241$ $L(p_2)=0.1725$	$L(p_1)=0.9593$ $L(p_2)=0.2553$
$n=81$	$L(p_1)=0.6630$ $L(p_2)=0.0294$	$L(p_1)=0.7738$ $L(p_2)=0.0563$	**$L(p_1)=0.8585$** **$L(p_2)=0.0985$**	$L(p_1)=0.9176$ $L(p_2)=0.1589$	$L(p_1)=0.9552$ $L(p_2)=0.2377$
$n=82$	$L(p_1)=0.6478$ $L(p_2)=0.0261$	$L(p_1)=0.7609$ $L(p_2)=0.0506$	$L(p_1)=0.8487$ $L(p_2)=0.0896$	$L(p_1)=0.9107$ $L(p_2)=0.1461$	$L(p_1)=0.9509$ $L(p_2)=0.2210$
$n=83$	$L(p_1)=0.6326$ $L(p_2)=0.0231$	$L(p_1)=0.7478$ $L(p_2)=0.0454$	$L(p_1)=0.8385$ $L(p_2)=0.0813$	$L(p_1)=0.9035$ $L(p_2)=0.1341$	$L(p_1)=0.9462$ $L(p_2)=0.2051$
$n=84$	$L(p_1)=0.6172$ $L(p_2)=0.0205$	$L(p_1)=0.7344$ $L(p_2)=0.0407$	$L(p_1)=0.8280$ $L(p_2)=0.0737$	$L(p_1)=0.8960$ $L(p_2)=0.1229$	$L(p_1)=0.9413$ $L(p_2)=0.1901$
$n=85$	$L(p_1)=0.6018$ $L(p_2)=0.0181$	$L(p_1)=0.7208$ $L(p_2)=0.0364$	$L(p_1)=0.8171$ $L(p_2)=0.0667$	$L(p_1)=0.8881$ $L(p_2)=0.1125$	$L(p_1)=0.9360$ $L(p_2)=0.1758$

Sampling plan $n=81$ and $c=12$ fulfil both conditions for groups A and B:

$$L(p_1)=0.8585;\ L(p_2)=0.0985.$$

It is further possible to use iterative method to find optimal sample sizes (n) and acceptable defective product limit (c) per different rates of expected defects in a batch of received ammunition parts. It is possible to build an example table for different sets of parameters (Table 5), which can be easily used and implemented inside ARMA 3 game engine at the step of ammunition preparation for "suppressive fire" missions, and could greatly optimize time needed and estimated quality of prepared ammunition.

Table 5

Sample size (n) and acceptable defective product limit (c) for defect rate (p)

Parameters	$p=0.01$	$p=0.02$	$p=0.03$	$p=0.05$	$p=0.1$	$p=0.15$
$n=20$	$c=1$	$c=1$	$c=2$	$c=2$	$c=3$	$c=5$
$n=40$	$c=1$	$c=1$	$c=3$	$c=3$	$c=4$	$c=7$
$n=100$	$c=3$	$c=4$	$c=6$	$c=7$	$c=15$	$c=20$
$n=150$	$c=4$	$c=6$	$c=8$	$c=10$	$c=20$	$c=27$

Chosen acceptance plans allow to efficiently and in a small amount of time check the quality for a large amount of ammunition batches, with the consideration of inspection error and recommended for quality control system for an ammunition preparation for "suppressive fire" missions.

3.3. Hypergeometric Distribution

Hypergeometric distribution plays a crucial role in acceptance sampling, particularly when evaluating attribute characteristics in a finite lot without replacement. This statistical model is essential for determining the probability of selecting defective or non-defective items, ensuring accurate quality assessments in batch inspection processes:

$$f(x)=\frac{C_x^{Nk}C_{n-x}^{Nq}}{C_n^N}, \quad (5)$$

where N – lot size; k – proportion defective in the lot; q – proportion effective in the lot; n – sample size; x – number of occurrences.

It is possible to say that in a batch of N parts there are actually k defective parts. If to take a random sample of size n (without replacement), then the probability that the sample will contain exactly x defective parts is described by the hypergeometric law:

$$P(X=x|k)=\frac{\binom{k}{x}\binom{N-k}{n-x}}{\binom{N}{n}}. \quad (6)$$

There is a need for the probability that there are no defective items in the sample ($x=0$), provided that there are exactly k defective items in the batch:

$$P(X=0|k)=\frac{\binom{k}{0}\binom{N-k}{n}}{\binom{N}{n}}=\frac{\binom{N-k}{n}}{\binom{N}{n}}. \quad (7)$$

It is possible to choose n so that for $k=6$ the probability of "not finding a single defective part" is ≤0.1. Formally:

$$P(X=0|k=6)=\frac{\binom{6}{0}\binom{100-6}{n}}{\binom{100}{n}}=\frac{\binom{94}{n}}{\binom{100}{n}}\le 0.1.$$

Therefore, if to check n parts and do not find a single defective one, then with a probability of at least 90 % it is possible to say that there are no more than 5 defective parts in the batch.

Using iterative method for $n=25$–40, it is possible to find value $P(X;\,k)$ for n that will fulfill that equation (Table 6).

Table 6

Chances of finding 0 defective parts for different sample sizes

n	$P(0;6)$	$P(0;5)$	$P(0;4)$	$P(0;3)$	$P(0;2)$	$P(0;1)$
25	0.168918	0.229246	0.309967	0.417594	0.560606	0.75
26	0.155405	0.213963	0.293435	0.400891	0.545657	0.74
27	0.142805	0.199506	0.277574	0.384638	0.530909	0.73
28	0.131067	0.185841	0.262364	0.368831	0.516364	0.72
29	0.10145	0.172936	0.247789	0.353463	0.50202	0.71
30	0.109992	0.160757	0.233829	0.338528	0.487879	0.7
31	**0.100564**	0.149275	0.220467	0.32402	0.473939	0.69
32	0.091819	0.138458	0.207686	0.309932	0.460202	0.68
33	0.083718	0.128277	0.19547	0.296259	0.446667	0.67
34	0.07622	0.118704	0.1838	0.282993	0.433333	0.66
35	0.069291	0.109711	0.17266	0.27013	0.420202	0.65
36	0.062895	0.101272	0.162035	0.257662	0.407273	0.64
37	0.056999	0.09336	0.151908	0.245584	0.394545	0.63
38	0.05157	0.085951	0.142263	0.23389	0.38202	0.62
39	0.04658	0.079019	0.133085	0.222573	0.369697	0.61
40	0.041998	0.072542	0.124358	0.211626	0.357576	0.6

Using sampling size $n=31$, it is possible with 90 % confidence to dismiss product with 6 or more defective units in a whole batch of artillery shells (product C) of $N=100$ units:

$$P(X=0|k=6)=\frac{\binom{94}{31}}{\binom{100}{31}}\le 0.1.$$

It is also possible to take into account the possibility of assembly error of artillery shells, while using the chosen type of acceptance plan.

Let's assume that there is an assembly error due to the imperfections in assembly equipment:

$$\mathrm{p}_a=0.002.$$

For a batch of N units, because of assembly error it is possible to assume that total amount of defective units will be equal:

$$k_t=k+k_a, \quad (8)$$

where k – number of defective units in the lot, k_a – number of defective units due to the assembly error:

$$k_a=p_a\cdot N, \quad (9)$$

where p_a – assembly error probability, N – total number of shells in a lot.

There is a need for the probability that there are $\le k_a$, defective items in the sample ($x=0,1,...,k_a$), provided that there are exactly k_t defective items in the batch:

$$P_t=\sum_{x=0}^{k_a}P(x|k_t)=\sum_{x=0}^{k_a}\frac{\binom{k_t}{x}\binom{N-k_t}{n-x}}{\binom{N}{n}}. \quad (10)$$

It is possible to choose n so that for k_t the probability of "finding less then k_a defective parts" is ≤0.1. Formally:

$$k_a=0.02\cdot100=2,$$

$$k_t=k+k_a=6+2=8,$$

$$P_t=\sum_{x=0}^{2}P(x|8)=\sum_{x=0}^{2}\frac{\binom{8}{x}\binom{100-8}{n-x}}{\binom{100}{n}}\le0.1.$$

Therefore, if to check n parts and did not find a single defective one, then with a probability of at least 90 % it is possible to say that there are no more than 5 defective parts in the batch.

Using iterative method for $n=40–60$, it is possible to find value $P(X; k)$ for n that will fulfill that equation (Table 7).

Table 7

Chances of finding $x=0–8$ defective parts for different sample sizes

n	$P(0, 8)$	$P(1, 8)$	$P(2, 8)$	$P(3, 8)$	$P(4, 8)$	$P(5, 8)$
40	0.01375	0.083016	0.209846	0.289969	0.239483	0.121002
41	0.011916	0.075164	0.198547	0.28679	0.247682	0.130918
42	0.0103	0.067862	0.187273	0.282677	0.255194	0.141053
43	0.00888	0.061093	0.17609	0.277681	0.261963	0.151357
44	0.007633	0.054836	0.165057	0.271859	0.267938	0.161774
45	0.006543	0.049072	0.154227	0.26527	0.273073	0.172246
46	0.005591	0.043778	0.143648	0.25798	0.277328	0.18271
47	0.004763	0.038932	0.133362	0.250054	0.280672	0.193103
48	0.004044	0.034509	0.123406	0.241561	0.28308	0.203355
49	0.003422	0.030485	0.113812	0.232573	0.284531	0.213398
50	0.002885	0.026838	0.104607	0.223162	0.285016	0.223162
51	0.002423	0.023542	0.095812	0.213398	0.284531	0.232573
52	0.002028	0.020575	0.087443	0.203355	0.28308	0.241561
53	**0.00169**	**0.017912**	**0.079513**	0.193103	0.280672	0.250054
54	0.001402	0.015532	0.07203	0.18271	0.277328	0.25798
55	0.001158	0.013412	0.064998	0.172246	0.273073	0.26527
56	0.000952	0.011532	0.058418	0.161774	0.267938	0.271859
57	0.000779	0.00987	0.052287	0.151357	0.261963	0.277681
58	0.000634	0.008409	0.046598	0.141053	0.255194	0.282677
59	0.000513	0.007128	0.041342	0.130918	0.247682	0.28679
60	0.000413	0.006011	0.036509	0.121002	0.239483	0.289969

Using sampling size $n=53$, it is possible to with 90 % confidence dismiss products with 8 or more defective units in a whole batch of artillery shells (product C) of $N=100$ units, while taking into the account the assembly error $p=0.02$.

Using this method, it is possible to find optimal sample sizes (n) per estimated defect rate. It is possible to build an example table for different sets of parameters (Table 8), which can be implemented and used inside game engine of ARMA 3 at the step of ammunition preparation for "destructive fire" missions to optimize time needed.

Table 8

Sample sizes (n) per estimated maximum of defective parts (k)

Parameters	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$
$N=50$	$n=21$	$n=18$	$n=15$	$n=13$	$n=12$	$n=10$
$N=100$	$n=42$	$n=35$	$n=31$	$n=27$	$n=24$	$n=21$
$N=150$	$n=63$	$n=53$	$n=46$	$n=40$	$n=36$	$n=32$
$N=200$	$n=85$	$n=71$	$n=61$	$n=54$	$n=48$	$n=43$
$N=250$	$n=106$	$n=89$	$n=77$	$n=67$	$n=60$	$n=54$

Because this sampling plan with a high confidence rejects low-quality batches, using it allows to efficiently validate for a higher quality of ammunition batches. But it will not be effective for a batch of medium or low quality, because it will invalidate most of the ammunition batches. That means, using a hypergeometric statistical quality control method is a best way to prepare for a "destroy" type of artillery missions, which require highest quality of ammunition.

3.4. Limitations of research and directions for its further development

Acceptance sampling is a useful quality control tool, but it has limitations. Since only a sample is inspected, defective lots may be accepted if defects are missed. If defects occur sporadically rather than consistently throughout a batch, there is a higher chance that a sample might not detect them, leading to the acceptance of faulty products. If the sample is not truly representative of the entire batch, the results may be misleading. Poor sampling techniques can lead to incorrect conclusions about product quality.

Implementing simulation for the statistical quality control methods in ammunition preparation directly enhances the effectiveness of artillery shots by ensuring that each round meets the operational requirements of the specific mission. The integration of hypergeometric and binomial distribution-based acceptance sampling optimizes ammunition quality, leading to several key improvements:

Increasing the effectiveness of shots. By matching the appropriate quality control methods to the specific demands of each artillery operation, the effectiveness of each shot is maximized, contributing to greater mission success, improved combat efficiency, and better resource management. These methods ensure that artillery forces can deliver accurate, consistent, and mission-ready firepower whenever required.

Practical applications in military simulators. By integrating statistical sampling techniques into a computer simulation, such as ARMA 3 and others, military analysts can accurately predict the effectiveness of artillery operations based on ammunition quality. This approach enables data-driven decision-making, optimizing both resource allocation and battlefield strategy while minimizing risks associated with defective ammunition.

Practical applications in real combat conditions. Proposed strategies allow to decrease the impact of bad ammunition quality in a real combat operation, in a reasonable amount of time, without the requirement of additional equipment.

Prospects for further research. By incorporating ammunition preparation and quality control simulation with can add it in any computer simulations, which allows to assess the impact of ammunition quality on combat effectiveness, refining how different acceptance sampling methods influence mission success. Optimize ammunition logistics and resource allocation, ensuring that units receive the right type and quantity of rounds for specific operations. And enhance training simulations for military personnel, allowing them to experience how ammunition reliability affects fire missions and decision-making under combat conditions.

4. Conclusions

In the realities of modern warfare new factors have emerged due to which a new problem has arisen, based on practical experience. It creates the need in additional validation step for all artillery ammunition parts. Modern computer simulations often ignore the problem of ammunition quality.

The proposed method allows to carry out quality control with a satisfactory degree of confidence, in a shorter amount of time, and could be performed in the harsh conditions of combat operations, without the need for additional equipment.

In this study, a computer simulation was developed and implemented, which allows to improve current state of existing artillery simulators, and add new ammunition quality control process tailored to the specific requirements of Suppressive Fire and Destructive Fire artillery operations. Statistical sampling methods were integrated into the simulation and made calculations, which help to enhance the reliability, efficiency, and adaptability of quality control procedures while ensuring mission success in a virtual battlefield environment.

For Destructive Fire missions, where precision, reliability, and maximum impact are critical, the simulation utilizes a hypergeometric distribution-based sampling model. This method ensures high-confidence rejection of low-quality batches, allowing only the highest-grade ammunition to be deployed. However, since this approach eliminates most medium- and low-quality batches, the simulation reveals its limited effectiveness in scenarios where a large quantity of ammunition is required with slightly relaxed quality constraints.

For Suppressive Fire missions, where sustained firepower and volume are prioritized over absolute precision, the simulation employs a binomial distribution-based acceptance sampling plan. This model allows for rapid quality assessment of large ammunition batches while accounting for inspection errors and realistic operational constraints. As demonstrated in the simulation, this method provides an efficient and practical solution for quality control in scenarios requiring continuous firepower over an extended period.

By integrating these acceptance sampling methods into the simulation, it is possible to ensure that each type of artillery operation receives ammunition suited to its specific needs, leading to improved operational effectiveness, optimized resource management, and realistic decision-making scenarios. Future research could focus on enhancing the simulation's realism by incorporating real-time data analytics, adaptive sampling algorithms, and environmental factors to further refine quality assurance strategies in artillery logistics and mission planning.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, including financial, personal, authorship, or any other, that could affect the study and its results presented in this article.

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Data availability

The paper has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating this work.

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