Electromagnetic Launcher Speed Control with a Multilevel Fast Triggering Time Algorithm (MFTTA)

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Abstract—Electromagnetic launchers (EMLs) can provide accurate speed control of a projectile compared to gun-powder based alternatives. However large-caliber launchers have several pulse power supply (PPS) modules connected in parallel to reach the required current levels. Determination of the triggering instants of these parallel PPS modules is a crucial part of the launch mechanism. The triggering instants does not only affect the exit velocity but also the forces on the armature which can lead to transition i.e. separation of the armature from the rails. In this study, a triggering sequence optimization method that is faster than other alternatives in the literature and take into account speed-dependent parasitic masses and transition phenomena. Real-coded genetic algorithm (RCGA) and Partial Swarm Optimization (PSO) are used to create benchmarks. 32 capacitive PPS modules with 8 MJ total energy is used. With the achieved accuracy and speed, this study offer: An effective speed control algorithm with several physical constraints.

Index Terms—Electromagnetic launchers (EMLs), Pulse Power Supplies (PPS), armature speed control.

I. INTRODUCTION

Electromagnetic launchers (EMLs) are electromechanical energy conversion machines that convert electrical energy to linear kinetic energy. The system consists of two parallel conducting rails, an armature and a non-conductive projectile and sabot petals that secure the projectile's correct positioning within the rails. The system is excited by pulse power supplies (PPS), which can supply currents in a few million-ampere range that creates a Lorentz force on the armature [1]–[3]. The force accelerates the launch package to a few thousand meters per second. Unlike explosive-based systems, EMLs inherently offer better velocity control for the projectile.

PPS's for EML applications are often capacitor-based topologies [4]. In order to produce a few MJ electrical energy, several capacitor-based PPS modules should be connected in parallel. Since there are many units in the PPS, each unit's triggering time affects the total discharge current waveform

[5]. Thus, timing sequence PPS should be optimized in order to enhance the performance of the EML. Optimization of the PPS unit's timing sequence though different objectives and constraints is a well-studied problem in the literature. However, most of them use evolutionary algorithms such as genetic algorithm (GA) and Particle Swarm Optimization (PSO). These algorithms are useful to find local minima even though there are multiple input features and non-linear behaviors between objectives and features. However, the cost is the excessive number of function evaluations.

The usage of GA for triggering time optimization problem (TTOP) has the following motivation: the relation between the desired rail current waveform and the set of triggering times is nonprogrammable or requires hardware modifications to control the output waveform shape [6]. The triggering time's nonprogrammable nature results in large numbers of input parameters, i.e., each triggering time becomes a parameter. Thus, GA has better performance on large dimensional input space so that it is a convenient way to use in TTOP [5]–[9]. However, the relation between rail current waveform and the set of triggering times in fact can be programmable in specific rail current shapes. For example, Zhang *et al.* [10] states that for a given magnitude of flat rail current, the set of triggering time that ensures the desired rail current is unique and can be calculated iteratively. The proposed iterative algorithm is compared with GA-based solutions of TTOP, and the iteration-based method has preferable effects on calculating timing sequence [11].

In this study, we proposed an iterative algorithm that calculates the set of triggering time for given muzzle velocity. The flat-top rail current waveform is targeted; however, it did not be considered a constraint to the optimization algorithm. The flatness of the rail current is obtained by an internal control algorithm, which reduced the optimization problem's complexity. Apart from other iterative-based solutions of TTOP in literature [10], [11], our model has an additional constraint on down-slope rail current, which reduces transition risks. Moreover, the study conducted with different capacitor voltage so that the vertex of the TTOP under given constraint is explained. The algorithm is compared with non-iterative algorithms in the literature, GA and PSO. These algorithms

TABLE I
EML DESIGN PARAMETERS AND LIMITATIONS.

Rail Height	70 mm
Rail Separation	70 mm
Rail Width	50 mm
Rail Length	5 m
Pre-load Distance	70 cm
Projectile Mass	500 g
Maximum Linear Current Density	32.5 kA/mm
Maximum Peak Current	2275 kA

are used to create benchmarks to show the computational load deficit when the proposed algorithm is used. For clarity, the EML design and limitations are used, which are listed in Table 1.

The organization of the paper is the following: In Section II, the literature survey of the TTOP is provided, and the main objectives and constraints of these problems are revealed. Then, the simulation model used in this study is explained in Section III. The proposed model is described and compared with the GA and PSO models in Section IV. Finally, the conclusions are exhibited in Section V.

II. LITERATURE SURVEY OF TTOP

Triggering strategy is one of the critical features that affect EML efficiency, and the systems' generated forces. Thus, TTOP is a well-studied topic in the literature. These studies can be divided into two parts in terms of their objectives. These are listed in the following subsections. Studies can be found in the Table 2.

TABLE II
LITERATURE SURVEY ON TRIGGERING TIME ALGORITHMS.

	Objective	Method	Constraints
[10]	Muzzle velocity	Iterative	-
[2]	Muzzle velocity	GA	Current
[8]	Max velocity, max efficiency	GA, NSGA-II	Acceleration
[9]	Max velocity, max efficiency	GA, NSGA-II	Current
[5]	Desired current waveform	GA	
[12]	Muzzle velocity	Harmony Search, ODM	Current

A. Optimizing the Triggering Times to Obtain the Maximum Muzzle Velocity

EML efficiency depends on the triggering strategy. Although the L' , one of the important parameter which determines the EML efficiency, is not dependent the triggering strategy, other parameters such as linear current density $\bar{J}_{\text{linear}}$, the muzzle current, I_{exit} have an influence on the launch mechanism. An example of such TTOP is given in (1). The objective of the problem is maximizing the muzzle/exit velocity denoted as v_{exit} . Constraints are adjusted considering the transition phenomena, which is linked heavily to the launch security. The transition phenomenon is described as the transition of solid contact into arcing contact. Multiple mechanisms cause transition [13]. One of them is the $\bar{J}_{\text{linear}}$. I_{max} refers to the maximum allowed rail current, which is related to rail dimension and the $\bar{J}_{\text{linear}}$. Therefore, for a pre-defined EML geometry and selected $\bar{J}_{\text{linear}}$, I_{max} can be introduced as a

constraint to the magnitude of the pulse shape current denoted as I_{ref} . I_{exit} is considered as another transition constraint. I_{exit} is responsible for the so-called "down-slope transition", which is reported by different studies in the literature. Wang *et al.* [14] reported that the down-slope transition occurs when the I_{exit} is lower than 90% of the I_{ref} . Satapaty *et al.* [15] made a statistical analysis based on the experiments and showed that the down-slope transition occurs when I_{exit} is lower than 80% of the I_{ref} . It should be noted that these studies were conducted with small and medium caliber EMLs, respectively.

$$\begin{aligned} \max \quad & v_{\text{exit}} \\ \text{subject to} \quad & I_{\text{ref}} \leq I_{\text{max}} \\ & I_{\text{exit}} \geq 0.5I_{\text{ref}} \\ & |I_{\text{rail}} - I_{\text{ref}}|_{\text{RMS}} \leq \epsilon I_{\text{ref}} \quad t \in [t_1, t_2] \end{aligned} \quad (1)$$

The third constraint is the deviation of the pulse current wave-shape. RMSE is used as an error measure, which is defined in (2). n represents the number of current samples. ϵ in the third constraint in the (1) is the allowed deviation in the I_{rail} . It should be in the form of a flat-top pulse shape. Sharp variations in the rail currents are undesirable due to voltage oscillations in the EML, which is considered as inductive load.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (I_{\text{ref}} - I_{\text{rail}})^2} \quad (2)$$

Zhengjun *et al.* [8] made a TTOP study that maximize v_{exit} and efficiency. Since two objectives are targeted, the Pareto frontier is used. The acceleration of the armature is constrained. The deviation of the pulse current shape, as well as I_{exit} is not considered. Yu *et al.* made another TTOP study that has the same objective as [8]. I_{ref} is constrained, considering the maximum allowed acceleration. The novelty of the simulation model, the addition of VSE and contact resistances, are introduced. However, I_{exit} and the quality of the pulse current waveform is not recognized. Moreover, both studies used an evolutionary algorithm that is computationally expensive.

B. Optimizing the Triggering Times to Ensure Desired Muzzle Velocity

Efficiency can be sacrificed when the tactical operation is deemed in EMLs. Therefore, TTOP should have different objectives rather than maximizing v_{exit} . An example of such TTOP is represented in (3). The objective of the TTOP is the diminishing the quadratic velocity error. l_1 norm/absolute error is not considered as a minimizer considering its non-differentiable nature. (3) shares the same constraints with (1).

$$\begin{aligned} \min \quad & (v_{\text{desired}} - v_{\text{exit}})^2 \\ \text{subject to} \quad & I_{\text{ref}} \leq I_{\text{max}} \\ & I_{\text{exit}} \geq 0.5I_{\text{ref}} \\ & |I_{\text{rail}} - I_{\text{ref}}|_{\text{RMS}} \leq \epsilon I_{\text{ref}} \quad t \in [t_1, t_2] \end{aligned} \quad (3)$$

Chao *et al.* [12] used a harmony search algorithm for TTOP. Desired muzzle velocity v_{desired} is targeted. I_{max} is used as an

constraint. However, I_{exit} is not considered. Zhang *et al.* [10] used an iterative algorithm rather than evolutionary algorithms for the TTOP. v_{desired} is targeted. The shape of the pulse rail current is constrained. However, the efficiency is not considered. Liu *et al.* maximized the efficiency with v_{defined} under the I_{max} constraint. However, I_{rail} does not consider the pulse waveform as well as the I_{exit} constraint.

III. THE SIMULATION MODEL

The detailed analysis of EMLs requires 3-D Finite Element Method (FEM) simulations. However, optimizations with 3-D FEM are time-consuming; thus, appropriate simplifications should be made to have reasonable computation time [16]. In this section, these simplifications and the construction of the 1-D EML model is explained. The EML can be modeled with an R-C circuit. The R-C circuit is illustrated in Fig. 1. R_{EML} and L_{EML} represent the total resistance and inductance of the EML, respectively. It should be noted that R_{EML} is dependent not only position but also frequency (f) and the armature velocity (v).

Fig. 1. The R-L approximation of the EML system. L_{EML} and R_{EML} defined as equivalent inductance and resistance of electromagnetic launcher.

In EMLs, there are mainly three major elements affecting the R_{EML} like in (4). The AC resistance, R_{ac} occurs when there is a change in the rail excitation current due to skin and proximity effects. The second element is the velocity skin effect resistance (R_{vse}), which happens at the trailing edge of the armature-rail contact interface and is highly dominant at high projectile velocities. The last element is the back-emf at the breach denoted as $\mathcal{E}$, which can be modeled as a resistor. (R_{emf}). Although back-emf is not a resistive component from a physical perspective, it can be modeled with a resistor from a mathematical perspective like in (5,6).

$$R_{\text{EML}} = R_{\text{vse}}(v) + R_{\text{ac}}(f) + R_{\text{emf}}(v) \quad (4)$$

$$\mathcal{E} = \frac{dL(t)}{dt}I(t) + L(t)\frac{dI(t)}{dt} \quad (5)$$

$$\mathcal{E} = R_{\text{emf}}I(t) + L(t)\frac{dI(t)}{dt} \quad (6)$$

As stated in [16] and [17] the L_{EML} has two components. L_{ext} is the inductance between the rails and L_{int} is the inductance component inside the rails. In (7) calculation of the

total inductance gradient (L') was presented. B equals to B_z due to symmetry. Multiplied with the number of turns (single turn in our case), the surface integral of B_z results in flux linkage λ . When λ is divided by the rail current results in the instantaneous inductance of the rails is obtained. In order to find the total transient inductance gradient, flux linkage λ was divided to I_{rail} , and the distance between the breach and the $B = 0$ contour line inside of the armature which is denoted by x_0 . The L_{EML} calculation was given in (8). The integration area and x_0 can be seen in Fig. 2.

$$L'_{\text{ext}} + L'_{\text{int}} = \frac{1}{2I_{\text{rail}}} \int |B_z| dA \quad (7)$$

$$L_{\text{EML}}(x) = (L'_{\text{ext}} + L'_{\text{int}})x \quad (8)$$

Fig. 2. Integration boundary and x_0 .

R'_{ac} , L'_{ext} and L'_{int} is found by calculating gradients while keeping the armature stationary in 3-D FEM. These gradients are used to create position-dependent lumped parameters updated with the armature motion in the 1-D model. R_{vse} was found by 2-D moving armature simulations. In the VSE calculation study, a DC was applied, and the simulation was repeated for different constant armature velocities. The total resistance of the rail is calculated using the ohmic loss calculation as in (10). However, DC resistance, as stated in (9), used to isolate R_{vse} as in (11). Hence an empiric formulation was developed and used during the simulation. In (9-11), the resistivity of the rails is denoted as ρ_{rail} . J_{rail} and $\|\cdot\|$ represents the current density inside the rails and l_2 norm, respectively.

$$R_{\text{rail}}(x) = \rho_{\text{rail}}xA \quad (9)$$

$$R_{\text{ac}}(x) = x \frac{1}{I(t)^2} \iiint_V \rho_{\text{rail}} \|J_{\text{rail}}(t)\|^2 dV \quad (10)$$

$$R_{\text{vse}}(v) = \frac{1}{I(t)^2} \iiint_V \rho_{\text{rail}} \|J_{\text{rail}}(t)\|^2 dV - \rho_{\text{rail}}xA \quad (11)$$

Due to the lack of a 3D body in the 1-D simulation environment, transients of L' and R_{ac} is not achievable. In [16], R_{ac} is relatively high during the early stages of the

launch compared to R_{vse} and R_{emf} , R_{vse} and R_{emf} are the dominating resistances after 500 m/s. Moreover, in our study, the flat-top current further reduces the skin effect; hence R_{ac} was neglected during the analysis. In this study, special attention to L' calculation is given due to precise transient modeling. A 3D FEM model is performed to investigate the following theorem, which is similar to the study in [16] and [17].

Theorem 3.1: Total inductance gradient ($L'_{ext} + L'_{int}$) is invariant from I_{ref} when pulse rail current is applied. The rise time of the rail currents kept constant, considering the rail currents form from identical PPS units.

The variation of L' with different rail current pulses needs to be analyzed. In Fig. 3 the rail geometry and in Fig. 4 the excitation currents are presented. According to Fig. 4, the total inductance gradient does not change for different pulse current excitations. In this figure, non-optimized I_{rail} is showed for better understanding of the third constraint of (1) and (3).

Fig. 3. Concentrated coil approach, breech to muzzle cross-section.

Fig. 4. Current excitation on the rails, resultant transient inductance gradients and non-optimized current waveform.

It is possible to consider the rails as a single turn concentrated coil where the effective distance between the rails changes due to the dependence of skin effect on the change in the rail excitation current. In Fig. 3 the distance between the

rails geometry is d_1 , the distances between the concentrated current and inner edge of the rails are d_2 and therefore the effective distance between the rails is $d_{coils} = d_1 + 2d_2$.

If there is a change in the magnitude of current (i.e. $\frac{dI}{dt}$), d_{coils} gets closer to d_1 since due to skin effect current concentrates on the inner surface of the rails (as in current rise at the first few ms.). However, as the current reaches to flat top of the waveform, the current distribution gets more homogeneous, and hence more flux-linkage (λ) is obtained. Moreover, since the change in total L' is independent of current pulse shape, the same L' can be used during 1-D modeling. Thus, there is no need for 3-D FEM simulation for accuracy of L' , when the triggering times are optimized.

IV. MULTI-LEVEL FAST TRIGGERING TIME ALGORITHM

Multiple capacitive PPS modules are used to achieve higher energized projectile in EML applications. Paralleling is applied to complete this task. An example of such a system is demonstrated with Fig. 5. 16 PPS modules are used. For larger-caliber as well as higher energy EMLs, the number of capacitive PPS unit is also increased. In this study, 32 capacitive PPS module is used for that purpose. Since there are multiple electrical excitation modules, there is N triggering time, which should be optimized. The design variables showed as following vector notation where i represent PPS module index and α represents the number of initial firing;

$$\vec{t} = \begin{pmatrix} t_\alpha \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ t_{32} \end{pmatrix} \quad 0 \leq t_i \leq 4\text{ms} \quad \forall i \in [\alpha, 32] \quad (12)$$

$$t_i = 0 \quad \forall i \in [1, \alpha] \quad (13)$$

MFTTA consists of two main parts. The first part is a hysteresis control of I_{rail} with the I_{ref} , which is the peak of the trapezoidal current waveform. Then, the algorithm determines how many modules to be fired at the beginning. The pulse current shape is conserved with a hysteresis control in the simulation model. The hysteresis control is made with COMSOL's Event interface, where the simulation can be stopped with predefined variable conditions. Therefore, when I_{rail} is below I_{ref} , the event interface is triggered and saves the time where this event happened. This time can be used as a new triggering time, since the new triggering can hold the I_{rail} at the I_{ref} level, thanks to the additional energy comes from the new PPS module. The second part of the MFTTA is responsible for the find the I_{ref} that ensures the $v_{desired}$. Each part is explained in the following subsections. The pseudo-code of the algorithm is given in Algorithm 1.

Fig. 5. The connection of pulse power supplies to EML. In this study 32 capacitive based PPS module connected parallel to EML

Fig. 6. PCSHC. The algorithm takes input as I_{ref} and give N amount triggering time which associated with a unique v_{exit} . The algorithm spend $N - M$ circuit simulation time for all obtaining triggering times.

A. Pulse Current Shape with Hysteresis Control(PCSHC)

The flowchart of the PCSHC is illustrated in Fig. 6. The first part is a hysteresis control of rail current with the given reference current I_{ref} which is the peak of the trapezoidal current waveform. Intermediate results of the hysteresis control is illustrated in Fig. 7. Then, the algorithm determines how many modules to be fired at the beginning. The rail current waveforms with various initial firing sequences are given in Fig. 8. The maximum current limit is determined by the maximum linear current density constraint. After selecting the

Algorithm 1 The Multi-Level Fast Triggering Time Algorithm.

Input: $v_{desired}$

Output: $[t_1 \dots t_N]$

Calculating Initial Firing:

- 1: Discretize I_{ref} with N_{min} and N_{max} (in Fig. 8)
- 2: Obtain pulse rail current which have magnitude I_{ref} using hysteresis control in the simulation (in Fig. 9)
- 3: Discretize v using previous step rail currents (in Fig. 10)
- 4: Find the I_{ref} interval (N_i and N_{i+1}) for $v_{desired}$
Line Search at the interval
- 5: Compute two intermediate points using golden ratio (Fig. 11a).
- 6: **while** $r_e < \epsilon$ **do**
- 7: **if** ($I_1 < I_2$) **then**
- 8: Change the lower bound; $I_L = I_2$ (Fig. 11b)
- 9: Carry the intermediate point to the next; $I_2 = I_1$
- 10: Calculate the new intermediate point, I'_1
- 11: **end if**
- 12: **if** ($I_2 < I_1$) **then**
- 13: Change the higher bound; $I_H = I_1$
- 14: Carry the intermediate point to the next; $I_1 = I_2$
- 15: Calculate the new intermediate point, I'_2
- 16: **end if**
- 17: compute relative error, r_e
- 18: compute the new distance ($I_H - I_L$)
- 19: **end while**
- 20: **return** $\vec{I}_{opt}$

number of initial firing modules, the algorithm tries to find the next triggering points which create pulse shaped rail current at I_{ref} . COMSOL's Event interface is used to build an hysteresis control. Simulation is aborted just after the new trigger point is generated to reduce the computation time. The results of the first part of the algorithm with respect to various I_{ref} values are given in Fig. 9. If the pulse power supply unit has N parallel modules and one simulation takes T time, after selecting the initially fired modules (denoted as M), firing instants of $N - M$ units need to be determined. This means that the simulation has to be repeated $N - M$ times for pulse current waveform which has a magnitude of I_{ref} . Since there is a stop condition in simulations, simulations are aborted immediately after finding the triggering instant, controller finds triggering sequence at $(N - M)t/2$ time, neglecting the convergence time of the simulation. Simulations take a few seconds since the study conducted in 1-D.

B. Determination of the Required I_{ref} for Desired Exit Velocity

The first part of the algorithm generates triggering sequence with given current limit I_{ref} . However, at this stage the I_{ref} for a unique projectile muzzle velocity is still unknown. For this purpose following theorem is proposed by [10].

Theorem 4.1: There exist a unique I_{ref} for given exit velocity. Therefore, there exists a unique set of triggering times for every exit velocity value.

Such a statement is true with the assumption of constant capacitor voltage and constant launch package mass. The

Fig. 7. Intermediate results of the pulse current algorithm. The algorithm search for trigger time which is defined as moment that rail current decreased from I_{ref} . Then, it restart the simulation with a new triggering time, and search for next. While iterations continue, the rail current becomes pulse shape current with increasing width.

Fig. 8. Peak current vs. number of modules triggered at $t=0$ ms. The dashed current lines exceeds the maximum current density in Table I.

effect of these parameters will also be discussed in the next sections. Exit velocity vs. amplitude of pulse current, I_{ref} , is given in Fig. 9. It is clear that exit velocity is a one-to-one function of I_{ref} . Moreover, the error function, which is defined as $I_{ref} - I_{ref}^*$, is a uni-modal function with the given boundaries. Therefore, a line search algorithm can be used for finding proper I_{ref} value. In this study, we used golden section search algorithm for line search method [18]. Some steps of the golden search algorithm is illustrated in Fig. 11. The performance of the golden section algorithm is given in Fig. 12.

After a few iterations, the relative error is reduced down to 0.1%. Considering that one function evaluation, which finds a set of triggering time for a given I_{ref} , takes 10 to 18 circuit simulations (depending on the number of design variable), the proposed algorithm requires a few tens of simulations for 1% relative error and one or two hundred simulations for 0.1% relative error. However, it should be noted that the performance parameter of the algorithm is relative error. Thus, the accuracy of the speed control is still heavily depends on the 1-D simulation accuracy. The scope of the paper includes a triggering strategy algorithm and

exclude the pure performance of the 1-D model. However, enhancements can be made with 1-D model and the proposed triggering algorithm can be applied directly.

Fig. 9. The results pulse current algorithm respect to different I_{ref} . N denoted as module number is taken 32. The capacitor voltage of the module are identical at 6500 V.

V. RESULTS

Two evolutionary algorithms are implemented to solve TTOP. These algorithms create not only benchmarks to the MFTTA but also some understandings about the effects of the constraints. The parameters we used in RCGA given as in Table 2. The parameters of PSO are given Table 3. The hyper-parameter optimization for these algorithms is skipped considering the scope of this study.

A GA is a meta-heuristic optimization algorithm that is inspired by the theory of natural evolution. The algorithm shows the process of natural selection where the fittest individuals are selected for the next generation. Elitism in the GA implies the best solution obtained for the current generation and have a pass to the next generation. Notably, it means keeping the best individual found intact for the next generation. Since it has a positive impact on the convergence of the algorithm, it is also

Fig. 10. Exit velocity vs amplitude of pulse current graph at $V_c = 6500$ V. This graph indicates that there exist a unique pulse shape current for all exit velocities.

(a) Initialization with the intermediate points.

(b) Narrowing the search distance when $(I_1 < I_2)$.

(c) Narrowing the search distance when $(I_2 < I_1)$

Fig. 11. Same steps of the golden search algorithm.

used in this study. The tournament selection parameter is the number of individuals that sorted as a group. These groups are used crossovers, which ensure the quality of the matches.

PSO is another “nature-inspired” meta-heuristic optimization algorithm like GAs. The communication between crowds of animals, such as birds and fish, such as finding a food source and avoiding predators, increases their speed of finding the optimal solution. In this application, “birds” are the triggering times and “the search for a food source” is an analogy for obtaining the $v_{\max}$.

Fig. 12. The performance of golden section line search algorithm. Noted that the golden section line search algorithm uses only one function evaluation at all iterations except the initial one. Considering that one function evaluation takes 10 to 18 circuit simulations, the proposed algorithm requires a few tens of iterations for 1% relative error and one or two hundred iterations for 0.1% relative error.

TABLE III
THE PARAMETERS OF RCGA

Population Size	50
Number of Generation	100
The number of design parameters	16
Elite Size	5
Tournament Selection	10
Crossover Rate	0.8
Mutation Rate	0.2

TABLE IV
THE PARAMETERS OF PSO

Population Size	50
Number of Generation	100
The number of design parameters	16
Maximum velocity	0.1 ms
Minimum velocity	-0.1 ms
Inertia	1
Damping Inertial Term	0.99
Social Acceleration Term	1.4962
Personal Acceleration Term	1.4962

Two different optimization studies are conducted with RCGA. These studies differ from their constraints. The $I_{\max}$ constraint is relaxed in one of the studies to show the effect. The convergence graphs are shown in Fig. 13 and 14. The objective of these studies is maximizing $v_{\max}$. The best individuals of the selected iterations are illustrated in Fig. 15

Fig. 13. Individuals of each generation and their cost values with RCGA with constraints. The population size looks like decrease after generations due to maximum current constraint.

Fig. 14. Individuals of each generation and their cost values with RCGA. No constraint applied. The purpose of this study is understanding of behaviour of system with respect to triggering times. After various iterations the maximum v_{exit} is 2723 m/s which corresponding to all triggering times are 0 s. However this result violate the maximum rail current constraint.

and 16. I_{rail} and the velocity curves are used to visualization for triggering times. When the I_{max} constraint is relaxed, the triggering time converges to all zero vector, as in Fig. 15. However, when violation of I_{max} is penalized the I_{rail} is nothing but the pulse current that have I_{max} length. This can be understand from Fig. 14.

The result of the PSO is demonstrated in Fig. 17. Each circle represents an individual/particle, and each color represent a generation. The movement of the particle is shown using an arrow. I_{max} constraint is applied. Therefore, the comparison between and RCGA and PSO in terms of convergence should be made between Fig. 13 and 17. Although both algorithms converge the same optimum solution, RCGA reach the opti-

Fig. 15. Initial intermediate and final steps of RCGA without constraint. It showed that the firing sequence converged to zero vector (indicating that all PPS modules triggered initial time step). However, this condition violate the maximum rail current constraint

Fig. 16. Initial intermediate and final steps of RCGA with constraint. The study showed that rail current becomes pulse current that have magnitude I_{max} to have maximum v_{exit} and maximum efficiency η .

imum solution at 46th iteration whereas PSO reach 11th. Thus, PSO outperformed RCGA in a TTOP. The comparison of the three algorithms in terms of computational load is represented in Table 5.

TABLE V
THE PERFORMANCE COMPARISON OF THE METHODS

	GA	PSO	MFTTA
Objective: $v_{desired}$	2500	950	160
Objective: v_{max}	2300	550	18 ²

¹ Each number represent the number of simulations/function evaluations for the given method.

² MFTTA use the information that for maximizing v_{max} , the I_{rail} should be pulse shaped current with the magnitude I_{max} .

The results showed that MFTTA outperformed GA and PSO in terms of computational load. The reason is that MFTTA has the ability to transform multiple input features (triggering times) to one input feature, I_{ref} . Since the search space dimension is reduced to one, and the error function is uni-modal, a simple line search algorithm can minimize the

Fig. 17. The result of Particle Swarm Optimization. The result are consistent with RCGA

error with a few iterations. In Fig. 18, different MFTTA results are illustrated to understand the behavior of various triggering strategies better. For a specified v_{exit} , there are multiple I_{rail} guarantees the v_{exit} and each of them has different PPS voltage denoted as V_c . This situation is illustrated in Fig. 19. Six different I_{ref} and their set of triggering times that guarantee 2153 m/s muzzle speed are obtained. The most efficient one is the one that has the lowest V_c . Consequently, this solution also has the lowest I_{exit} . Therefore, there is a trade-off between efficiency and the risk of transition.

Fig. 18. Variation of peak current and projectile to input power efficiency vs. projectile speed for different capacitor charge voltages.

VI. DISCUSSION

This study is conducted with the motivation of searching a triggering strategy under different EML objectives. Although

Fig. 19. Various pulse currents with different capacitor voltages which satisfy desired exit velocity $v_{exit} = 2153$ m/s. Decrease in capacitor voltage for fixed exit velocity leads to increase at pulse current magnitude I_{ref} and decrease in exit current I_{exit} . Efficiency increases when the capacitor voltage decreased however increase in I_{ref} and decrease in I_{exit} increase the risk of the transition. [15]

the simulation model's accuracy is sought, the fundamental novelty of the study is the methodology of obtaining triggering times. The methodology can be applied to different 1-D simulation models as well as 3-D FEM simulations.

Hyper-parameter optimization of the benchmark methods (GA and PSO) is skipped. The main goal of adding these methods to the study is to give a figure of merit the advantages of the iterative methods in TTOP. Moreover, the convergence of these methods gives insights about the behavior of triggering times when the maximum efficiency is targeted.

Although the down-slope transition is linked with I_{exit} between 80-90% of I_{ref} in the literature, there are some reported experiments with lower I_{exit} percentage no-transition [17]. Thus, in this study the constraint is settled a lower value 40%. However, this parameter can be re-adjusted considering the new I_{exit} constraint.

VII. CONCLUSION

In this study TTOP solved by various algorithms such as RCGA, PSO and the proposed iterative method, MFTTA. In this paper not only the comparison of iterative and evolutionary method but also the novelty of 1-D simulation model introduced. The optimization results are used to show trade offs of different triggering strategies. These remarks are listed as following;

- 1) Without constraints, the triggering times at TTOP converge to zero vector which indicates all PPS modules triggered at initial time step to have maximum v_{exit} . However, resulting rail current exceeds the maximum rail current limit which has harmful effect on the rails.

- 2) Considering the current constraints, the rail current converge to pulse shaped current which have magnitude $I_{\max}$ when the objective is $v_{\max}$.
- 3) Evolutionary based algorithms are slower than iterative based algorithms for triggering time calculation of EML's. With increasing module number of PPS the performance of evolutionary algorithms become even worse due to necessity of increasing the number of individuals and generations. Iterative based computation is more robust to the increase in the module number.
- 4) The uniqueness of I_{ref} with the given exit velocity is valid if and only if the capacitor voltage and launch package mass are fixed. Therefore, there must an optimum I_{ref} that satisfies the desired launch package exit velocity and increases the overall system efficiency and satisfy other transition constraints.
- 5) For the same desired exit velocity, it is possible to generate multiple current pulse wave-forms as in Fig. 19. As the capacitor voltage decreases, the launch efficiency increases, the peak current increases and the exit current decreases. Increasing the peak and decreasing exit current result in transition between armature-rail interface. Therefore, a compromise has to be made during selection of launch triggering sequence and capacitor charge voltages.

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