Agent Based Modelling of the Equipment Battle Damage

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***Abstract*—To model equipment battle damage needs reasonably to describe complexity feature of battle damage process. So an agents/space approach was established from Agent Based Modelling. In this scheme agent technology was used to model anti-tank projectiles and its damage effect, and equipment model was treated as three dimension simulating space, and dynamic damage relation was modeled by interaction of agents and space. Furthermore, damaging experiment was carried out, a neural network module was trained with experiment data and embedded into Piercing_Agent. At last a prototype simulating system of equipment battle damage was developed on Mason platform, and simulating result was validated through real war data and physical experiment data.**

***Index Terms*—damage model, agents/space approach, neural network, validation of simulating**

I. Introduction

Reasonable equipment battle damage law may provide an important foundation to many problems such as readiness materiel, support scheme and so on. Damage mechanism of equipment lies in residuary energy, namely anti-tank projectile after piercing armor damage the inner component of equipment [1], which includes debris behind armor (BAD) or shock wave or burning. To one equipment, damage state may be a random event. When damaged equipment reaches some limit, battle damage must be presented some law.

The researcher approach is combination of computer model and physical experiment. According to system engineer theory, battle damage system was partitioned into two elements of anti-tank projectiles and equipment target. When modeling equipment target, hull and inner component may be described including its structure, geometry and physics attribute such as aimed probability, vulnerability threshold and degraded function. As to anti-tank projectiles, its damage effect was fixed on debris behind armor which is main damage factor to inner component, and BAD parameter is a key to model projectiles effect.

The interaction of anti-tank projectiles and equipment target may be disassembled to three stages as initiate interacting, piercing armor and damaging inner component. The difficulties of armored equipment battle damage modeling were as following:

(1) Under campaigning environment, equipment shoot by projectiles was affected by many factors. Dynamics and uncertainty features in initiative interacting become a difficulty in battle damage modeling.

(2) Piercing armor is a very complex process. To nonlinearity relation in aimed condition and BAD parameter, there is no an available approach in domestic and overseas research.

(3) Battle damage modeling needs precise equipment model. It needs to describe not only equipment structure but also the damaged state and grade of inner component.

(4) Battle damage and physical experiment data present imperfect, inaccurate and fuzzy-bound feature. The battle damage model must melt these experiment data in reasonable approach.

As far as simulating model be concerned, complexity character of this process became remarkable obstacle. Therefore the focus of this problem lies in selecting suitable modeling approach to duplicate real battle damage system as complexity viewpoint. Mathematics model and traditional numeric model are deficient in matching three dimensions equipment model, dynamic interaction behavior and debris behind armor (BAD) of anti-tank projectiles [2]. Nowadays, ABM (Agent-based Modeling) became a prevalent technology to complex system on many fields [3]. Our work tries to explore a new modeling approach suitable to armored equipment battle damage form ABM.

II. Equipment Battle damage Model Architecture From ABM

A. Exploring Modeling Approach form ABM

Nowadays, ABM plays a prevalent role in complex system. From current ABM case based on complex adaptive system (CAS) theory in reference [4][5][6][7],

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two features may be found. First the entity defined as agent is not fixed on the alive but be schemed in schedule. Second space was imported into model, the interaction of agent and space became the center of system. Therefore armored equipment. Under Mason platform and agents/space architecture, the micro battle damage simulating system of armored equipment was built (sees fig.1).

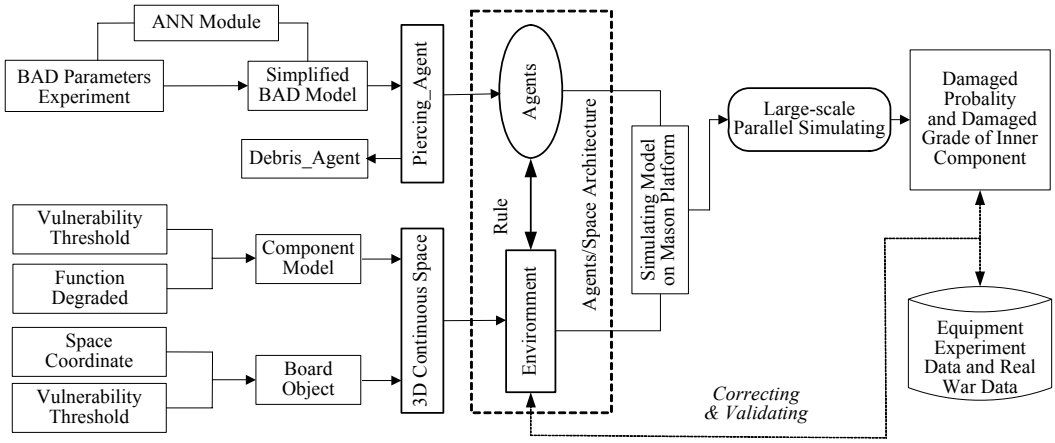

Figure1. Model architecture of armored equipment battle damage

we may try to construct an Agents/Space approach, in which agent may included all kinds of entities and space model was imported in system researched.

Obviously Agents/Space architecture may provide a universal and intuitional approach, and more abundant modeling capability than ABM. This approach decomposed system as agent, object, environment and rule. Agent represents the entity taking complex behavior, and object represents the fixed entity. The core of agents/space lies in Agent Behavior Model describing interaction of agent and environment (from production system to complex arithmetic), and Space Model(adopted by cellular automation, continuous space and so on).The theory base of this architecture is complex adaptive system (CAS) by J.Holland who is the founder of genetics arithmetic. CAS emphasized to decompose system as many agents and combine them into a multi-agent system by environment, and involved that the complex interacting behavior of inner system was simulated dynamically, and the inner state of agent or environment was gathered as system law.

To develop target system on existing platform may be beneficial in avoiding foundational work, enhancing progress of development and reusing model. Some ABM platforms may sustain agents/space architecture such as Swarm, Mason, Repast and Netlogo in some extent [8][9]. To choose platform lie in balancing between developing convenience and modeling capability.

B. Equipment Damage Model Architecture on Agent/Space approach

To modeling armored equipment battle damage on Agents/Space approach, anti-tank projectile and its damage effect behind armor may be modeled by agent technology, equipment may be treated as model environment damage relation may be modeled by interacting of agent and space. Mason platform may integrate computational model on java and 3D continuous space, which may sustain battle damage model of

- **Anti-tank projectile and its effect**

Anti-tank projectile and its damage effect behind armor have been modeled by agent, two kinds of agents should be developed including of Piercing_Agent to projectile and Debris_Agent to single debris of BAD.

a)Piercing_Agent's behavior includes in aiming equipment and controlling the direction and energy scatter of BAD. Its main behavior was modeled as following:

Choosing an aimed board: Because of war complexity, this relation takes on uncertain feature, in which distribution relies on campaign fashion. Here, an experience formula was adopted for general campaign as following [10]:

$$\rho(\theta_1 \sim \theta_2) = 0.1[\Delta\theta/360 + 0.596(\cos\theta_1 + \cos\theta_2) + 1.157] \quad (1)$$

Eq. (1) presents the aimed probability of equipment ρ in polar coordinates, the center of equipment is as polar origin o, direction of going forward is as polar axis, counter-clockwise angle with polar axis is as $\theta(+)$.

Damage effect behind armor: After piercing armor a damaging debris field was shaped as ellipse taper. There is no a feasible way for BAD model, experiential parameters were often adopted as following:

$$< \delta, \phi_c, \mu_\theta, \sigma_\theta, \mu_m, \sigma_m > \quad (2)$$

In this formula δ is a turn angle of BAD center line, ϕ_c is opening angle. μ_θ and σ_θ are distributing parameters of debris moving direction to BAD center line. μ_m and σ_m are distributing parameters of debris quantity with θ (on the assumption of normal distribution).

A neural network module on physical experiment will be introduced into Piercing_Agent to verify this simplified parameters model in section 3.

b) Debris_Agent represents single debris in BAD, which behavior includes moving in equipment, damaging inner component and destroying its self.

Moving track: based on line equation the arithmetic of Debris_Agent moving track is as following:

$$x = x_0 + t \cdot \cos\{[\ 360° - (\theta_s \pm \delta)] - (\theta_c \pm \delta) \pm \phi\}$$
$$y = y_0 + t \cdot \cos[(\ \theta_s \pm \delta) \pm \phi]$$
$$z = z_0 + t \cdot \cos\{[\ 90° - (\theta_c \pm \delta)] + \theta_c + 360° \times r_7\} \quad (3)$$

In the equation, (x0, y0, z0) is coordinate of aimed origin, θs is horizontal incidence angel to vertical axis, θc is vertical incidence angel to horizontal plane, δ is a turning angel to normal line, φ is crossing angel of this track and center line of BAD, r_7 is random of even distributation.

On this track arithmetic a simulating step was given, Debris_Agent may move in equipment. Inspecting arithmetic in Mason platform can be used to detect front component.

Distinguish damaged: P_{hk} represents damaged probability of component hit by debris. While P_{hk} equal 1, the target was damaged. While P_{hk} equal 0, the target was not damaged.

$$\begin{cases} p_{hk} = 1 \text{ while } e_s \geq H_s \\ p_{hk} = 0 \text{ while } e_s < H_s \end{cases} \quad (4)$$

In this equation e_s is kinetic energy of debris, Hs is equivalent thickness of this section.

- **Equipment environment**

To build equipment model, board and inner component were defined in 3D continuous space computational model of Mason platform, which may control the position of piercing projectile and its effect at the same time.

a)Hull of equipment may be partitioned as boards, every board was created through inheriting Shape3D class from Java 3D, meanwhile board class should mention normal vector, boundary angle and thickness of this board. The attribute of board class may be defined as following:

BoardAttributes（Point[4], AimedBoundaryAngle, ThicknessofBoard, NormalAngle）.

In this definition *Point[4]* represents four peak of board, *AimedBoundaryAngle* is boundary angel, *ThicknessofBoard* is thickness of this board, *NormalAngle* is normal vector of this board.

b)Inner component was represented by a group of cell, and every cell takes on regular geometry. Obviously these components bear 3D space structure and discrete attribute and state value. To build this model, component was partitioned a group of cell, then vulnerability threshold and damage grade of cell were defined.

Attribute of every cell may be defined as following:

CellAttributes（Position[3],VulnerabilityThreshold, DamagedGrade）.

In this definition *Position[3]* represents space position of cell, *VulnerabilityThreshold* represents vulnerability threshold of this part, *DamagedGrade* represents damage grade of component damaged.

As to component composed of a group of cell, attributes value of cell may be defined on its position in component. Attribute of every component may be defined as following:

BFIAttributes（NumbersofBFICell，isDamaged，DamagedGrade，aListofCell，DamagedTime）。

In this definition *NumbersofBFICell* is number of cell, *isDamaged* represents damaged or not damaged, *DamagedGrade* represents damage grade of this component, *aListofCell* represents cell collection controlled, *DamagedTime* represents damaged time of this component.

III.NEURAL NETWORKVERIFYING MODULE INNER PIECING_AGENT

Neural network may remedy data deficiency and mapping nonlinearity relation [11]. Here neural network computational model and BAD parameter experiment data were combined to complexity feature of BAD and aimed condition.

A. BAD Parameter Experiment

During firing against armored equipment with projectile, a homogeneous steel armor plate has been vertically fixed on target frame. Soap board is a block of CrMo alloy steel sheet and three blocks of AlSi alloy aluminum sheet, which thickness is 2mm. The steel sheet has been fixed after target board 1.8m, every aluminum sheet was fixed backward as 1.2m interval, and sandbag wall was set to collect remainder in the end. Flying debris has been shot by high speed camera as velocity of 4000 frame per second. Experiment scene sees Figure.2. Debris scattering in soap board sees Figure.3.

Figure2. Real scene of BAD parameter experiment

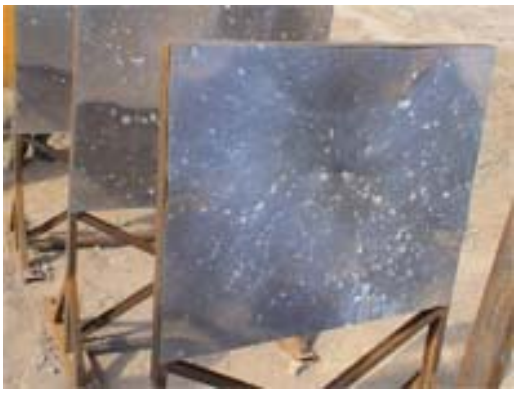

Figure 3. Debris scattering in soap board

BAD shape and debris kill capacity may be analysed through this experiment. Hole pierced in soap board was reclaimed and analysed statistically, general conclusion may be concluded as following: ①BAD was shaped as ellipse taper after armor being pierced, which long axis

is in vertical direction and peak is in the back of aimed position. ②scatter field resembles as normal distribution from main shoot center. ③there is a turn angel between BAD center line and incidence direction.

Experiment conclusion above show experiential model in section II may reflect general character of BAD. Scientific result needs a dynastically variational BAD model with aimed condition in order to reflect the truth situation of equipment damaged in battlefield. So BAD parameter experiment was done for observing situation of different armor thickness and vertical or some angle incidence condition, experiment data sees table 1(segmental data).

TABLE I.

BAD PARAMETER DATA VARIED WITH AIMED CONDITION

No.	Aimed condition			BAD parameter							
	v_0($m\cdot s^{-1}$)	α(°)	h(mm)	δ(°)	φ_c(°)	μ_θ(°)	σ_θ(°)	μ_m(g)	σ_m(g)	N_m	$\rho_{m\theta}$
1	1725	0	50	0.18	26	10.8325	20.3569	1.554	12.486	120	0.2391
2	1711	0	50	0.46	22	10.1184	14.8324	0.607	1.9015	158	0.1701
3	1698	30	50	2.64	33	12.7096	45.9145	0.551	2.8252	120	0.2021
4	1683	45	50	2.98	31	14.096	10.440	0.233	10.236	91	0.0601
5	1731	30	50	1.09	14	6.2103	23.1424	1.321	8.954	203	0.212
6	1634	0	250	2.01	25	9.2112	13.4562	0.235	7.2654	95	0.214

Aimed condition includes three parameters as aimed velocity v_0, cross angel α between incidence direction and armor normal vector, armor thickness h in table 1. BAD parameter includes six parameters as turn angel of BAD center line δ, opening angle of length axis ϕ_c, expectation value μ_θ and variance σ_θ of debris scatter angel, expectation value μ_m and variance σ_m of debris quality, debris number N_m and relativity coefficient $\rho_{m\theta}$ of debris quality and distributing angel.

According to experiment data several conclusion may be found: ①scatter area of BAD embody an increasing trend with aimed velocity, and there is a scale relation between long and short axis of ellipse taper. ②BAD scatter field of incline piercing is more wider than vertical piercing, and BAD shape is identical on the whole. ③turn angel embody a decrescent trend with aimed velocity increasing. ④if debris collected less than 0-10mm^2 area was treated as small debris, small debris will account for 80-90%. Debris quality follows normal distribution, and debris velocity is increasing with aimed velocity. ⑤there is a weak relativity between debris quality and scatter angel, so the two variables may be treated as independence.

Based on experiment conclusion above, BAD complexity feature should be meet to guarantee credibility of simulating system, namely to realize a dynamic continuous variational BAD model with different aimed condition.

B. Designing neural network verifying module

Neural network model was introduced to map relation between aimed condition and BAD parameters. Input parameters of this model include armor thickness, aimed velocity and incidence angel. Output parameters include turn angle of BAD center line, BAD opening angle, expectation and variance of debris scatter angle, expectation and variance of debris quality.

BP neural network with one hidden layer may map any continuous function [12], so a three-layer neural network model was adopted. Based on experiential formula [13] initial hidden node was set, then node number was adjusted on forecasting precision and converging velocity. at last a 3×11×6 neural network model was constructed. On practice data and inner relation tansig function was adopted in input and output layer, and logsig function was adopted in middle layer.

On this model additory momentum arithmetic was adopted to network learning, namely a variable proportional to near weight variance was added to weight variable, and new weight and threshold were produced on backpropagation arithmetic. Both error effect in gradient direction and error effect in curved surface trend were taken into account. The adjust formula to weight and threshold is as following:

$$\Delta W_{ij}(k+1) = (1-m_c)\eta\delta_i p_i + m_c \Delta W_{ij}(\mathrm{k}) \quad (4)$$

$$\Delta \mathrm{b}_i(k+1) = (1-m_c)\eta\delta_i + m_c \Delta \mathrm{b}_i(\mathrm{k}) \quad (5)$$

In two formulas, k represents training time, η represents network learning efficiency, p_j represents the i output vector, δ_i represents error propagating coefficient, m_c represents momentum factor about 0.95.

C. Importing Verifying Arithmetic into Simulating System

Piercing_Agent of anti-tank projectiles includes behaviors of apperceiving aimed condition and responding a BAD field with damage capability. As to BAD model, experiential values were adopted to describe BAD parameters in section II. In our research work BAD parameter experiment was done under typical condition, offset between physical experiment and experiential values were calculated, then neural network was trained with aimed condition and offset value. The verifying index Y from neural network output was used

to adjust BAD model parameter, which format is as following:

$$Y =< \delta_{ANN}, \phi_{cANN}, \mu_{\theta ANN}, \sigma_{\theta ANN}, \mu_{mANN}, \sigma_{mANN} > \quad (6)$$

In this formula δ_{ANN} is a verifying value to turn angle of BAD center line, φ_{cANN} is a verifying value to opening angle, $\mu_{\theta ANN}$ and $\sigma_{\theta ANN}$ is verifying value to debris distributing parameters, μ_{mANN} and σ_{mANN} is verifying value to distributing parameters of debris quantity.

This verifying module of neural network may be imported into simulating system through Joone（Java Object Oriented Neural Network）, which is a development tool of neural network on Java. Joone is open source project in sourceforget.net, through its component a neural network may be realized in IDE environment. In research work a neural network class was developed on Joone function, including of normalizing experiment data and training network model and saving trained network as file method. In simulating experiment process aimed condition was input neural network, the verifying value to BAD parameter was obtained, which was iterated on BAD model parameters to realize verifying.

In Piercing Agent the macro rule of BAD field was reflected through experiential value, and adaptability to error was built up through neural network computeral model and BAD parameter physical experiment. The complexity feature of this process was realized through a responding agent [14], the inner state of Piercing_Agent sees Figure 4.

and damaging inner component. EquipmentEnvironment is a collection of board and inner component, every component was consisted of a group of cell, in which attribution rest with its position.

DPModelWithUI is visualizing class inheriting GUIState, which bond DPModel to portrayals and display to realize visualization. Three dimensions scenes may be visualized on Mason of Java3D. A series of standard portrayals were provided on Mason, which may realize BAD visualization. As to equipment with boards and inner components, visualization was realized through inheriting SimplePortral3D superclass. Simulating scene of this model sees fig.5. In order to inspect inner component damage, hull of equipment was treated as line frame. Left figure show BAD while the foreside was aimed. Right figure shows the aimed cell turned its colors. Simulating scene may be drag and rotate to inspect on different view.

DPBatchModel was used to large-scale batch simulating that damage probability distributation was acquired. Only the equipment parameters and the experiement value of BAD were input model as data file, it may start DPModel to simulate battle damage. As to simulating result, Mason don't provide special statistic class, in this model JFreeChart was used. Fig.6 provides change curve of inner component so that the trend of damage may be observed to control simulation, namely simulation was closed when the trend near some value. Fig.7 provides damage probability histogram of components so that contrast analysis may be executed.

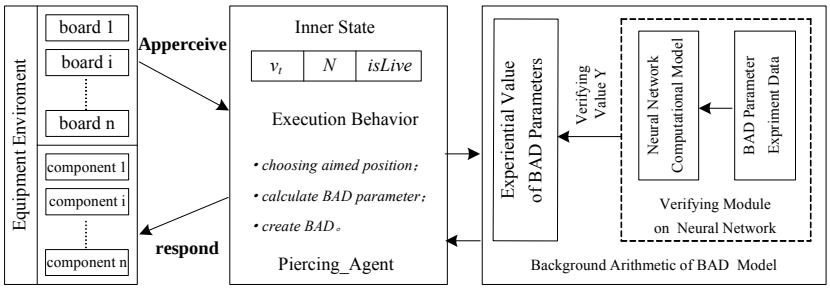

Figure 4. Piercing_Agent inner state and verifying arithmetic

IV. Model Implementing And Result Validating

A. Model Implementing

Battle damage model of armored equipment was consisted of two sections on Mason architecture. DPModel is basic model presenting interaction of projectile and equipment, which is self-inclusive class and inherits SimState superclass. Besides there is a visualizing module DPModelWithUI and a top control module BatchDPModel for batch simulation.

In DPModel starting simulation, stepping schedule and shutting program may be realized by Mason panel. EquipmentEnvironment and PeriecingAgent are two basic objects of DPModel. PeriecingAgent' behaviors include piercing armor and controlling the debris field behind armor. DebrisAgent is a new object after hull pierced, which behaviors include moving in equipment

Simulating data may be output from background as data file for further analysis with special statistic software.

B. Validation of Simulating System

The initial condition as equipment type, threat format and aimed probability were fixed on. We do experiment in Windows XP and 3.0G CPU and 2G internal memory, and obtain simulating result in hypothesis. Furthermore simulating experiment was executed more times, simulating data may constructed stylebook data space. Stylebook data was contrasted with real war data and experiment data of real equipment, simulating system may be validated.

(1) Contrast with real war data

Contrast of simulating result and real war data sees Table II (segmental data).

From table above simulating result is greater than real war data. Many factors such as campaign fashion, campaign environment, equipment type and anti-tank

projectile may bring about difference. But this conclusion may assist Validation of simulating system.

(2) Contrast with experiment data of real equipment

In experiment data of real equipment, nose armor, turret side and turret face were typical aimed region. Simulating result in similar condition was obtained through adjusting aimed probability. Contrast of simulating result and experiment data sees Table III (segmental data). Simulating result was less than experiment data, book-style quality of physical experiment lead to this difference.

From analysis above, simulating result was greater than real war data and less than experiment data of real equipment. We conclude that validation of simulating

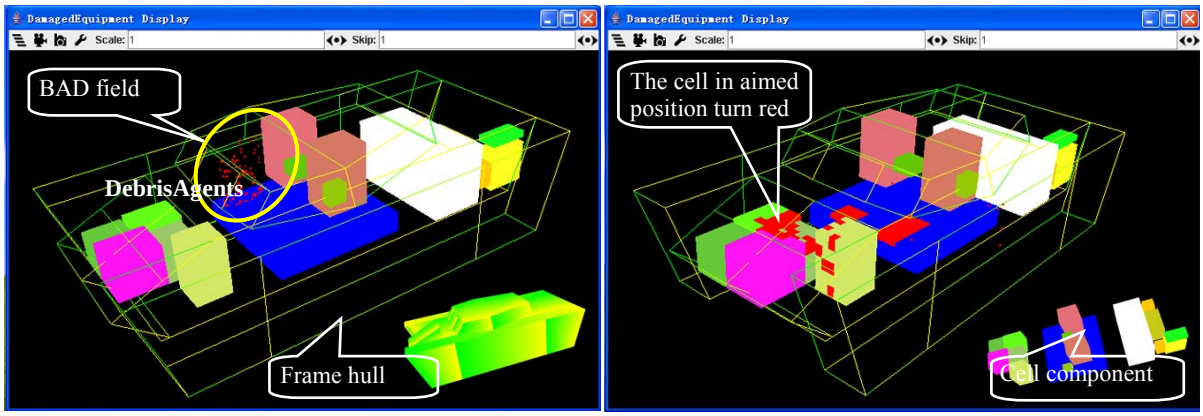

Figure 5. Simulating scene of armored equipment battle damage model

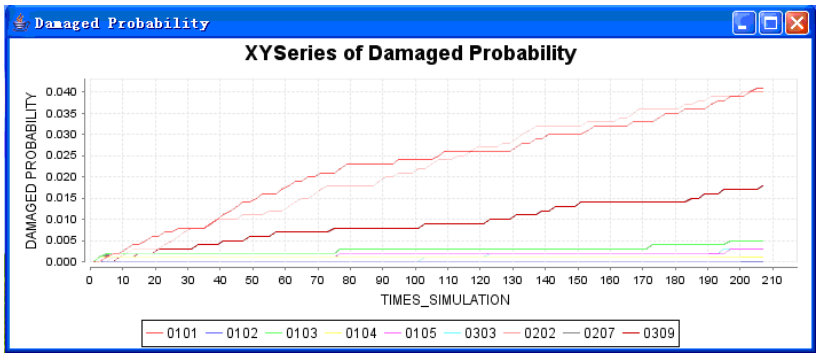

Figure 6. XYSeries of component damaged probability with simulating time

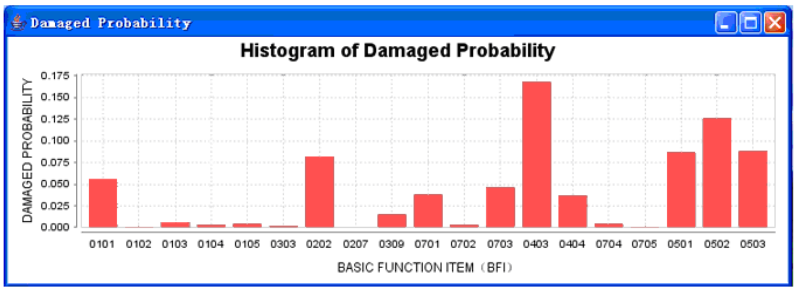

Figure 7. Histogram of component damaged probability

TABLE II.

CONTRAST OF SIMULATING RESULT AND REAL WAR DATA

Component number	0101	0102	0103	0104	0202	0704	0705
Simulating result	0.184	0.40	0.025	0.0060	0.229	0.014	0.204
	0.186	0.10	0.024	0.011	0.236	0.016	0.202
	0.163	0.10	0.019	0.0050	0.171	0.0090	0.100
	0.196	0.050	0.026	0.012	0.229	0.018	0.109
Real war data	0.0902	0.0452	0.00496	0.003	0.0896	0.01264	0.1086

TABLE III.

CONTRAST OF SIMULATING RESULT AND EXPERIMENT DATA OF REAL EQUIPMENT

Component number	0101	0202	0309	0501	0502	0503
Simulating result	0.245	0.02	0.016	0.227	0.032	0.236
	0.265	0.016	0.017	0.242	0.033	0.251
	0.241	0.071	0.014	0.227	0.030	0.18
	0.219	0.014	0.063	0.249	0.032	0.233
Experiment data of real equipment	0.294	0.091	0.091	0.336	0.051	0.345

system may be accepted. Meanwhile simulating result near experiment data of real equipment, and comparative error between them is about 20%, not surpass 50%, which show validation of simulation system.

V. CONCLUSIONS

On the feature of armored equipment battle damage, an agents/space approach was put forward. Armored equipment battle damage model was constructed, neural network module on experiment data was imported, and prototype simulating system was developed on Mason platform. Simulating system was validated through contrast with historic war data and experiment data of real equipment. Research result show an agents/space approach for battle damage embodies more flexible, and which provides more abundant expression capacity in dynamically interacting of projectile and equipment, parallel damaging of BAD swarm, three-dimension calculating and simulating result visualizing and so on.

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