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Application of numerical simulation for the estimation of die life after repeated hot forging work cycles

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Abstract

Die life estimation in hot forging processes is a compelling challenge, due to the number of factors, mainly wear and plastic deformation induced by thermal effects (tempering). The extent of the heating-cooling cycle and the steady state die temperature are known only after hundredth of work cycles. In the paper a realistic work sequence of repeated forging is simulated by the Finite Elements Method on a symmetrical workpiece geometry, for ease of calculation. Tool wear and tempering-induced deformation are estimated along the complete die life cycle, with the help of Neural Network Regression.

Keywords: Finite Elelements Method; Neural Network; Design of Experiments; Nonlinear Optimization

1. Introduction

The prediction of hot forging die life is an open research subject because there are several damaging factors that influence the wear and the failure of forging dies, as much as there are several process parameters that can control the insurgence of failure or reduce the wear rate. The main reasons for die substitution are abrasive wear, plastic deformation, fatigue cracks either mechanical or thermal [1]. The damaging factors are thermal shocks, load cycles, pressures exceeding yield stress of the die.

Typical service life of dies ranges between 10,000 and 50,000 cycles, but early die failures can occur. If there are not die failures, the die life is terminated when there are excessive unconformities in the shape of the final product, because of cracks on the product surface, because of difficult part extraction from the die [2]. It is apparent that the exact number of cycles defining the die life can be a question of choice among different production technicians.

The industrial interest for models that predict die life is considerable as dies in hot forging have a short life span, so die replacement is one or the main cost item in the production of forged components. Furthermore, die life can vary significantly during production, introducing cost variability.

Unfortunately, the parameters affecting production are numerous and many of them are difficult to control particularly if the factory is adopting manual production.

There is another factor that is responsible for the variability of die life, even when the same die materials are employed in the same factory and all the main process parameters are unchanged: the transient nature of the process. During repeated forging blows, die temperature increases because of the heat exchanged with the workpiece and because of the heat generated by plastic deformation. After several blows temperature tends to an asymptotic steady state value. Elapsed time between two blows and the employ of lubricant have the effect of increasing the time before the steady state condition is reached. The arrests during the shift change take back the die to the initial preheating temperature. Therefore, it is possible to claim that dies spend the most part of their life in transient conditions.

Experiments on fatigue usually repeat an identical fatigue cycle. Finite Elements (FE) Simulation of the process usually reproduces the process with nominal temperature conditions: the uniform preheating temperature of the dies and the work

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temperature of the part. The knowledge of the actual temperature figures is important not only for the thermal fatigue estimation but also to evaluate the amount of plastic deformation of the die that is generated when some zones of the die reach the tempering threshold.

It is very difficult to estimate correctly the transient rate, but it is possible to reproduce the transient phenomenon by a repeated simulation of the same forging process. In this way the zones of the die that are more likely to overcome failure can be easily spotted. Present analysis cannot give a realistic approximation of the transient duration, continuously variable in factories that adopt manual production. Therefore, the results cannot fit with real measures directly. The fitting to predict die life is therefore operated by training a Neural Network (NN).

In present study, FEM simulations were executed on an axisymmetric steel disk that represents one of the most common forged products. Simulations were executed for different values of disturbance factors. NN was trained, validated by additional set of tests data and eventually used to create a complete response surface to feed the optimization procedure.

Then several cycles of forging were simulated in succession leaving the heat flow between dies and part and outside of the die. The main damaging factors on the die were reported along the forging cycles and their steady state value was estimated by extrapolation of the given points on the curves. As a matter of fact, the simulation of all the thousands forging cycles along the full life of the die is unpractical (not impossible in a research study, but unthinkable as an industrial procedure).

In section 2 the damaging models used for the study are discussed, in section 3 the Neural Network inference is described. Section 4 deals with the case study description and the assumptions made to simulate repeated forging cycles. Section 5 presents the results and discusses the outcomes of the extrapolated figures.

The method was developed having as a target the applicability in the context of industrial process design, so paying attention to easy implementation and to computational time requirements. NN allow to replicate the expert reasoning based on the experience.

2. Damaging models of forging dies

2.1. Process parameters

The process parameters involved in hot forging and their role have been subject of investigation by [3] and [4]. They can be clustered under the following main groups [5]:

- Product geometry
- Product material
- Tooling
- Machine
- Process
- Tool-workpiece interface effects

Every group is composed by several parameters, each of them needing thorough investigation to understand its effect on the different quality and performance indicators and to define the guidelines for their optimal setting. As an example, flash allowance has important and conflictive effects on both the die filling and the die life [6]. Several models have been proposed to design the flash land. [7] compared 6 models, used them to design the flash land and verified the results by FEM simulation. They chose one model focusing on the minimization of die wear, but they recognized that, considering all the outputs, there was not a clear winner. In table 1 the most significant parameters are listed, concerning the process and the tool-workpiece interface.

Table 1. Selection of the most significant process parameters

Group	Parameter	Metric	Controlled?
Process	Workpiece's initial temperature	°C	Design
	Die temperature	°C	Design
	Time in air	s	Disturbance
	Time in open die	s	Disturbance
	Forging sequence	-	Design
	Die-part centering	mm	Disturbance
	Kinematics	-	Process
Interface	Friction coefficient	-	Design
	Heat conduction	°C	Design
	Lubrication properties	mm	Design

It is easy to understand the level of complexity when the parameters are considered all together. An additional difficulty is due to the difficulty in controlling all the referred parameters. Workpiece and die temperature are defined at design stage but could change, due to the waiting time before forging and to the variability of the heating procedure.

The amount of time spent on the die before the blow is widely variable and should be considered more a disturbance than an input parameter for the process.

Therefore, the standard procedure adopted in most of companies is to adopt proven functioning sets of parameters, making changes only on the process variables taken one by one. Recently, some authors propose to use the possibility of executing FEM simulations to look for optimal values of process variables, as in [8] or in [9]. In [10], FEM is used to concurrently optimize both process and product, obviously on a reduced number of variables.

The optimization procedure is deeply related to the objective of the optimization. Some study researches the minimization of the plastic deformation energy, others the under-filling of the die, the die wear, the folding defects and so on.

The complexity of global multi-objective optimization of every factor in the process is so high that several authors prefer to develop empirical expert systems to assist in the design phase [11] and [12]. These systems are trained with the support of a campaign of experiments. Sometimes expert systems are implemented as fuzzy inference rules [13]. Thus, the complexity of the problem is so high that nearly all the case studies present in literature are limited to 2D axisymmetric processes.

2.2. Damage models

The list of damaging mechanisms for the steel dies is long: abrasive and adhesive wear, oxidation, fatigue cracking, thermal and mechanical fatigue, plastic deformation. Only a few of them can be described by a predictive model, while the others rely on the results of experiments on the field.

It is generally believed [2] that abrasive wear accounts for 70% of the times the dies go out of service, while plastic deformation is responsible for the 25% of the cases.

The other degradation mechanisms are significant but don't lead to the termination of die service life. In the following the study will focus only on abrasive wear and plastic deformation models.

Abrasive wear on every point on the surface of the die can be calculated using the Archard model [14]:

$$W = \frac{k}{3h} \int_{tcycle} \mu p v_s dt \qquad (1)$$

where W is the wear traction, k a wear coefficient, μ the friction coefficient, p the normal pressure on the die surface, v_s the sliding velocity, h the HRC hardness of the die at the work temperature. Dimensionless coefficient k can be determined experimentally. Several authors adopt a value of $1.3 \cdot 10^{-4}$ for steel tools. The amount of wear that can be accepted before terminating die service life is left to factory choice.

The heating-cooling cycle on the die impacts not only in term of fatigue, but also through the softening of the metal tool. As a consequence, the die could undergo a tempering effect and its strength reduces under plastic yield stress. Pressure on the die can produce plastic deformation, making the die unable to comply with process specifications.

The equivalent temperature is the most significant value to consider in the models of plastic deformation induced on the die by tempering. If T_{max} and T_{min} are the highest and lowest temperature reached on the same die point, a convenient expression of T_{eq} is given by (2):

$$T_{eq} = \frac{2T_{max} + T_{min}}{3} \qquad (2)$$

The effect of tempering on the hardness of steel is given by the Holloman-Jaffe parameter M (3):

$$M = T(C + \log t), \qquad (3)$$

where T is the tempering temperature, to be replaced by T_{eq}, t is the tempering time and C is an empirical constant function of carbon concentration in the tool.

For H13 tool steel it is possible to find the value of M using the following diagram (provided by [1]), as a function of equivalent temperature and yield stress.

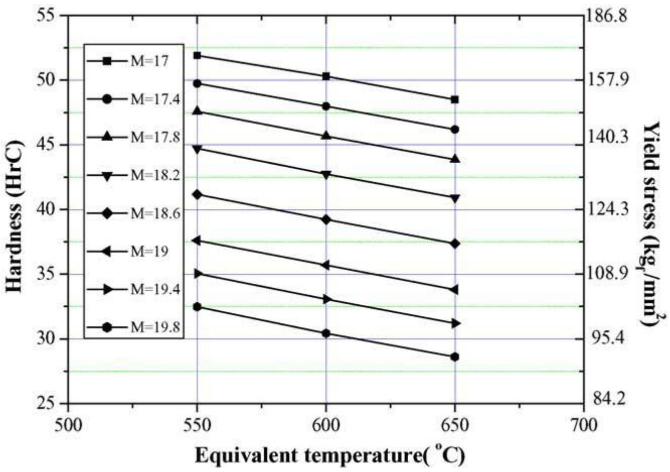

Fig. 1. Main tempering curves of H13 (from [1]).

The length of the die life before exceeding plastic deformation can be calculated using (4):

$$t_h = \exp\left(\frac{1000\, M_y}{T_{eq}} - C\right) \qquad (4)$$

In (4) t_h is the die life, M_y is the M value for which die hardness reaches critical hardness and C is the empirical constant used in (3).

It is apparent that every action that increases the equivalent temperature worsens the die life due to plastic deformation. Every action that increases the workpiece temperature improves the die life following abrasive wear.

3. The NN optimization procedure

The NN is trained on examples obtained executing a set of FEM simulations that are selected using the DOE methodology. The implementation of DOE, used in present study, is described in [14].

The reason for choosing NN instead of a regression model is the following. Regression model shape is constrained by the need of being able to fit it with polynomial regression or kriging. It means that, to obtain fair results, the function should be linear or quadratic, possibly without interactions among the variables.

The NN, conversely can be trained with whatsoever number of input factors (design parameters and disturbances as well) without imposing constraints on the shape of the response surface (the metamodel). Furthermore, it is possible to train the NN with input distributed in a non-regular way. After the first iteration of the algorithm it is therefore possible to refine the NN just in the area near the optimum, without the constraints posed by DOE construction.

3.1 Neural network design

The capability of the NN model to generalize regarding unknown data depends on several factors such as appropriate selection of input–output parameters of the system, distribution of the input–output dataset, and format of the input–output dataset presentation to the NN.

Accordingly, four steps were followed in the development of the NN model: (i) input–output dataset collection, (ii) input–output dataset pre-processing, (iii) NN design and training, and (iv) NN performance evaluation.

The optimal NN architecture was determined after several simulation trials. Diverse configurations of NNs were trained to identify the best arrangement for the prediction of flank wear. The parameters that were changed among the different configurations are the following:

- - number of nodes in the hidden layers;
- - number of hidden layers;
- - activation function of the node neurons.

In particular, to predict the T_{eq} 3, three diverse NN configurations were constructed and tested: NN5, NN8 and NN15 with 5, 8 and 15 nodes in the hidden layer, respectively. While, to predict the wear_t value, two different NN configurations were constructed and tested: NN3 and NN5 with 3 and 5 nodes in the hidden layer, respectively

In all tested NN configurations, the input layer had three nodes to receive the feature vector (Tp, Td and f) while the output layer had only one node to predict the T_{eq} or wear_t,.

The number of hidden layers was set equal to one and the number of hidden nodes was chosen according to a ''cascade learning'' procedure [15]: hidden units are added one at a time until an acceptable training speed is achieved. The hidden nodes were initially set equal to four and further nodes were added incrementally. The addition of hidden nodes continued until there was no significant progress in the NN performance.

To set up the NN models, the NNet toolbox of the Matlab software package was used. In particular, the Levenberg–Marquardt backpropagation algorithm was adopted for its performance in terms of rapid network error convergence and good reliability.

For optimal NN architecture configuration, weights and thresholds were randomly initialized between -1 and +1. Learning coefficients were: learning rate between input and hidden layer: 0.3, learning rate between hidden and output layer: 0.15, momentum: 0.4. The learning rule was the Normal Cumulative Delta Rule and the transfer function applied to the nodes was the sigmoid function $f(x) = 1/(1 + e^x)$ [16-20].

The number of learning steps for a complete training was set at 2000 on the basis of the time to convergence. Epoch size, i.e. the number of training presentations between weight updates, was set at 100.

4. Case study: die life in the extrusion of a forged disk

The case study is a C22 disk obtained in two steps by extrusion forging. The first step is the blocking phase. After flash removal, it is followed by a finishing step. The maximum die wear is found in the blocking phase that therefore is subjected to optimization. In this test of the method, only the parameters of the process and of the interface were considered, together with the disturbances variables. Fig. 2 shows the forged part and the dies.

The original process is executed on a 6.3MN crank press, 250mm/s ram velocity, the workpiece temperature is 1200°C, the dry lubricant is graphite with water vapor for a friction factor of 0.4. Both dies are H13 - AISI steel with ion nitride surface treatment and are pre-heated to 200°C. The flash is 3mm thick.

The process has been chosen as a benchmark because the FEM simulation is in good agreement with the experiment. The coupled thermos-mechanical simulation is executed with the QForm3D software from Quantor.

The temperature in the workpiece and in the die changes consistently during forging. In Fig.3 it is possible to see that die temperature after the first blow rises to a maximum of 669°C.

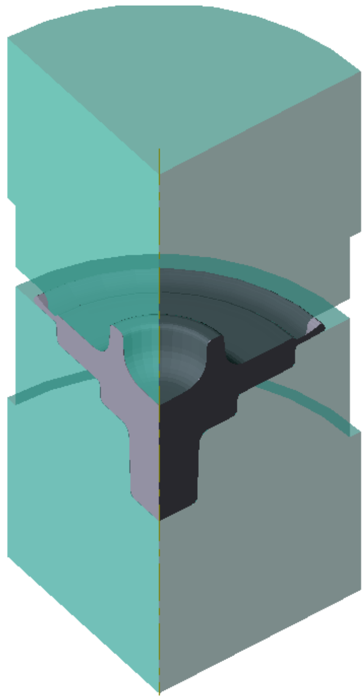

Fig. 2. The forged part inside the dies at the end of first forging blow.

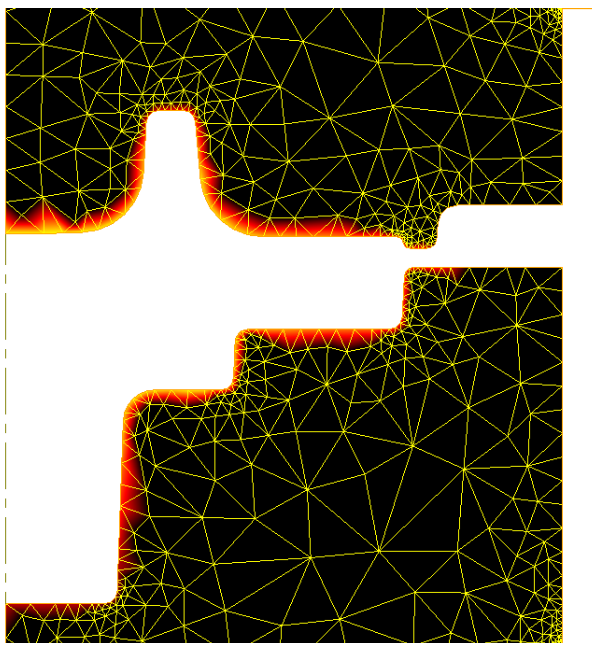

Fig. 3. The temperature on the die at the end of first forging blow (min 199°C, max 669°C).

The simulation was repeated several times, changing the workpiece but transferring on the new dies the exact temperature figures at the end of the preceding cycle. The elastic deformation of the dies and the stress distribution was not transferred from one cycle to the following because stress is released after part extraction. Tempering effects on the die in terms of decreasing hardness were not simulated, even if it was possible. The simulation was therefore decoupled. The forging was simulated considering the die as a rigid body, then the pressure distribution on the surface of the die is just used to estimate the abrasive wear. This choice was made because small die deformations are important only to determine the exact geometry of the forged part but are irrelevant on the die damaging study. After 10 cycles the simulation was arrested, and further values are obtained by extrapolation. Actual forging cycle should be less steep, as there is a variable cooling time between two consecutive blows. Cooling time has been assumed constant as 10 seconds. Thus, it is unrealistic to expect that the forging operator be able to keep a constant pace of loading-unloading the workpiece on the press.

Fig. 4 shows the maximum, minimum and equivalent temperature trend on the die. It also shows the predicted temperatures after 50 cycles, using logarithmic regression. The regressions have R^2 greater than 0.98. The regression results are still not satisfying. The asymptotic temperature isn't reached, contrary to real process. The maximum temperature that the die could reach is the workpiece surface temperature, if there isn't additional cooling action from the lubricant. The number of blows necessary to stabilize the temperature on the die is very high, even in actual production and it is impossible to simulate all the blows. The position on the upper die, the most solicited, of the maximum plastic deformation area and of the maximum abrasive wear zone are different. Plastic deformation is usually in the flat part of the die, while abrasion is maximum in the outward curvature radii. This phenomenon is clearly visible in Fig.5, that present die temperature and die abrasion as false colors in correspondence to the last simulated cycle, the tenth.

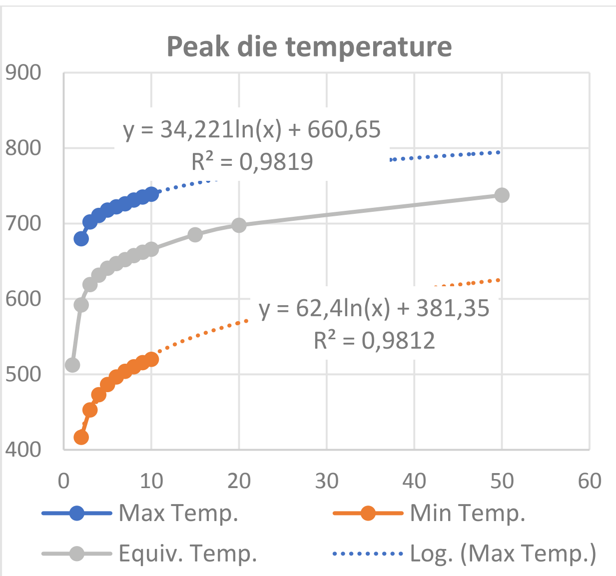

Fig. 4. Temperatures on the die after every blow: first 10 simulated and following estimated through logarithmic regression.

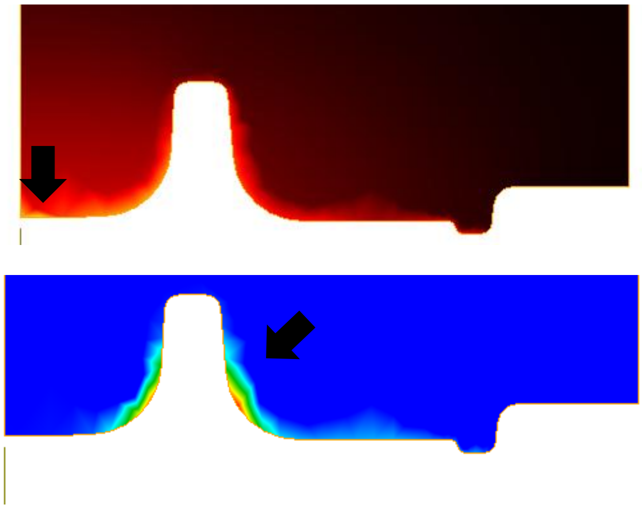

Fig. 5. Position on the upper die after 10 cycles of a) maximum temperature (666°C), cause of plastic deformation; b) maximum abrasive wear ($7.1 \cdot 10^{-4}$)

In Fig. 6 it is calculated the estimated die life due to plastic deformation, expressed as number of cycles before die substitution. Model parameters have values taken from literature, therefore die life figures should be considered as indication of a trend more than for their exact value.

It wasn't possible way to match these figures with actual production because there isn't a constant cooling time and there are breaks after every work-hour. It is probable that in actual production, the dies are in permanent transient state, reverting cyclically to initial values during the hour breaks.

Even so, the results are impressive. After the first forging cycle, tempering did not happen and there is no evidence of plastic deformation of the die. After the tenth cycle, die life is comparable with the expected figures for this forging operation. As we did not reach a steady state value of temperature, die life keeps reducing to very low values. Which value should be taken for realistic before experiments is impossible to determine at the design stage.

Even if we were unable to determine the steady state die temperature (if there is really such value in actual production), the results show that using the equivalent temperature of the first blow to predict the die life because of tempering effects leads to underestimate the damage mechanism.

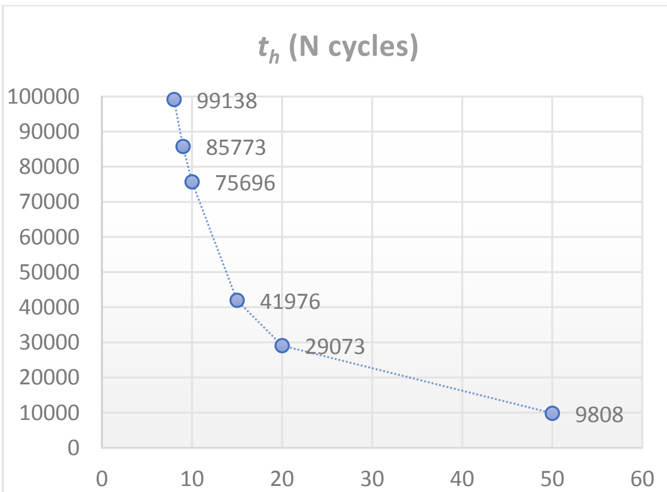

Fig. 6. Die life due to plastic deformation as a function of the number of consecutive repeated cycles.

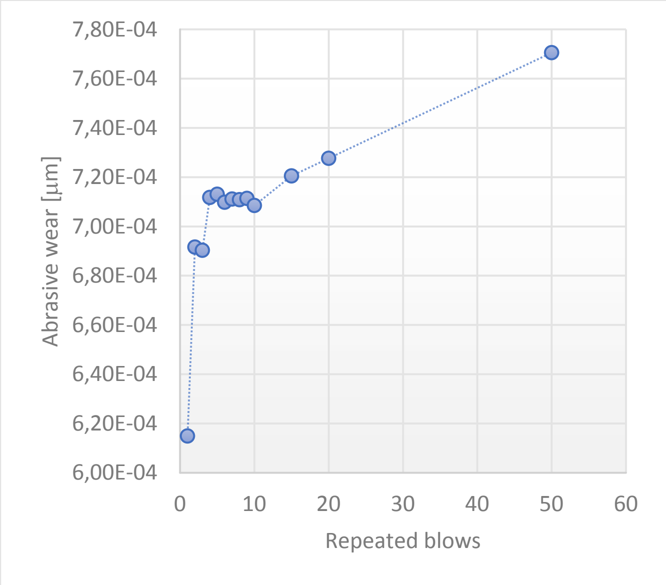

Fig. 7. Die wear due to abrasion in a single cycle.

Fig. 7 is the abrasive wear after each forging cycle. The figure is less impressive but there is still a non-negligible increase of the wear in the order of 15% between the first and the tenth cycle. Increase in the temperature of the die reduces its hardness and intensifies the abrasion effects.

5. Conclusions

Die life estimation in hot forging processes is a compelling challenge, due to the number of variable and often non-completely known process factors involved. To be able to predict die life in the design phase, before manufacturing the die leads to significant production saving. Therefore, the study focused on the main damaging mechanisms of the die: plastic deformation and abrasive wear. The die reduces its hardness with the increase of its temperature and this affects both damaging mechanisms.

The extent of the heating-cooling cycle and the steady state die temperature are known only after several work cycles. In the paper a realistic work sequence of repeated forging is simulated by the Finite Elements Method. The simulation sensitivity to different process parameters was validated using Neural Network Regression.

Damage models were used to calculate die life using the data after the first or after several forging cycles. Results obtained are so different that it is questionable if it makes sense any longer to try to predict die damaging after one simulation and using nominal values of the parameters, like it is done in the industrial practice.

Further developments of the research will be the training of the net using dataset obtained by experiments and using it to predict the damage evolution on the dies without having to execute lengthy and expensive repeated simulations.

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