Materials Research Proceedings 28 (2023) 649-656 https://doi.org/10.21741/9781644902479-70

Parametric identification on a dynamic behavior model for a forging machine

DURAND Camille[1,a *], SONG Heyu[1,b] and BIGOT Régis[1,c]

[1]Arts et Metiers Institute of Technology, Université de Lorraine, LCFC, HESAM Université, F-57070 Metz, France

[a]camille.durand@ensam.eu, [b]heyu.song@ensam.eu, [c]regis.bigot@ensam.eu

Keywords: Target Function, Sensitivity Study, Optimization Methods, Dynamic Behavior Model, Screw Press

Abstract. Dynamic models using masses, dampers and springs have been developed to represent the behavior of energy piloted machines. These models were proven to estimate more accurately the required amount of energy to forge a part. But how to identify the parameters of the model to accurately represent the behavior of a specific machine? In this study, the case of a strike without billet on a screw press is investigated, different target functions are tested to identify the model parameters and a sensitivity study of the optimization is performed. Results are encouraging.

Introduction

For forging processes using energy limited machines, such as hammers or screw presses, it is difficult to accurately predict the amount of energy that the billet actually absorbs as plastic deformation. This is due to energy losses caused by the dynamic behavior of the machines. That is why some dynamic models of forging machines were developed: first, models with masses and springs for gravity drop hammer [1,2] and then models with dampers in parallel with springs [3, 4]. For these models, the parameters were theoretically identified based on machine specifications. But nowadays, with the development of high-speed cameras, stereo vision systems and sensors, further experimental investigations are possible on forging hammers. For example, impact velocity was measured on a counter blow hammer and thus kinetic energy was deduced to determine blow efficiency [5,6]. Moreover, Yoneyama [7] was able to monitor the load, the pressure, the friction and the contact temperature while upsetting steel billets on a gravity drop hammer. Different sensors technologies to monitor ram displacement and load were also compared in the case of a screw press [8]. And finally, a dynamic model consisting in a spring-mass-damper model, was experimentally determined for a forging hammer [9]. To identify the parameters of such an experimentally based model, numerical optimization methods are required. And to guaranty the unicity, the accuracy and the reliability of the identified parameters, the target function has to be well defined [10] and a sensitivity study can be performed.

In this study, the method developed in a previous work to determine a dynamic model based on experiments [9] will be applied on a screw press. Once the model determined, a parametric identification will be run with different targets functions and results will be analyzed. Based on the analysis, a target function is chosen and a sensitivity study is conducted to ensure a proper model determination.

The Production System and its Dynamic Model

The focus is set on the screw press of the Vulcain Platform in Metz (Fig. 1.a). It is a direct drive screw press SPR 400 from Lasco, with a maximal energy of 28.9kJ for a maximal speed of 680 mm/s. A specific toolholder is mounted on the press, that allows the monitoring of the forging load, thanks to a load sensor embedded in the lower die, and the monitoring of the ram displacement, thanks to three laser sensors attached to the lower die, in addition to the magnetic encoder of the press [11].

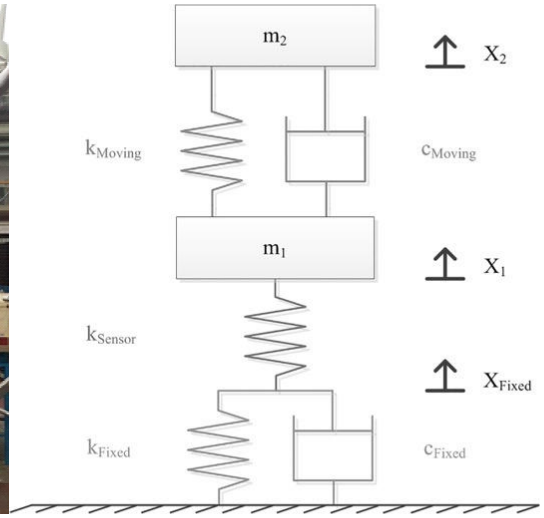

Fig. 1. a) the screw press b) the model of the screw press and its tool during a bare strike without billet.

An experimental campaign was launched to determine the dynamic model called the BIM model [9] of the screw press. Knowing the initial conditions and recording the load in function of the time for bare strikes (without billet), the model can be determined according to the method described in [9]. A Fast Fourier Transform (FFT) is performed on the load signal recorded during the strike (Fig. 2). As the impact duration is very short, it is not possible to have an analysis with a lot of frequency levels. Even though, two peaks are identified, thus a model with two degrees of freedom will be able to describe the dynamic behavior of the screw press (Fig. 1.b). The initial impact speed is known to be 365 mm/s. The load sensor is considered in the model thanks to the k_{sensor} spring and its value is set to $3.3997.10^{10}$ N/m as given by the supplier.

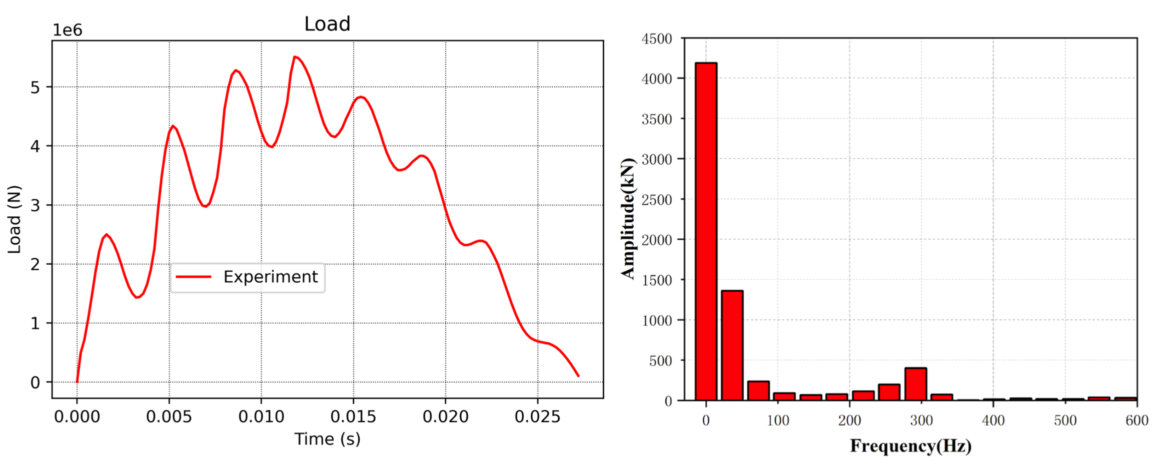

Fig. 2. a) the load signal measured by the sensor embedded in the lower die b) the FFT of the load.

Parametric Identification

Once the model defined, the parameters (m_1, m_2, k_{fixed}, k_{moving}, c_{fixed}, c_{moving}) have to be identified thanks to optimization algorithms. The optimizations were programed using Python. First, a target function was defined with a least square method only applied on the load in function of the time,

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but in most of the cases the second vibration mode was lost. So, the FFT was also included in the target function. To ensure a good identification, three different target functions were analyzed using least squares (1) or gradient descent algorithms (2)(3) [10]:

$$CF1\ (load, FFT) = f \cdot \sum_{i=1}^{n} \frac{\left(load_i^{exp} - load_i^{sim}\right)^2}{\|load^{exp}\|^2} + (1-f) \cdot \sum_{1=1}^{m} \frac{\left(FFT_i^{exp} - FFT_i^{sim}\right)^2}{\|FFT^{exp}\|^2} \tag{1}$$

$$CF2\ (load, FFT) = f \cdot \sqrt{\sum_{i=1}^{n} \frac{\left(load_i^{exp} - load_i^{sim}\right)^2}{\|load^{exp}\|^2}} + (1-f) \cdot \sqrt{\sum_{1=1}^{m} \frac{\left(FFT_i^{exp} - FFT_i^{sim}\right)^2}{\|FFT^{exp}\|^2}} \tag{2}$$

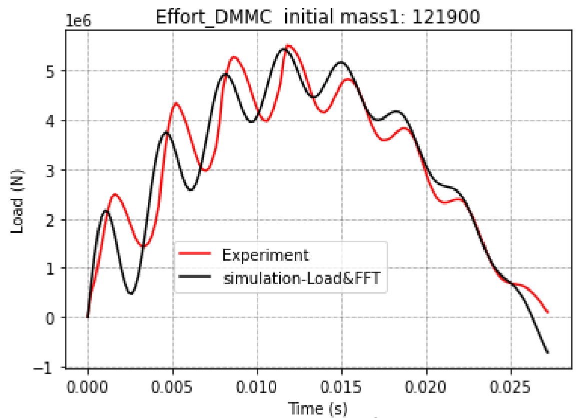
$$CF3\ (load, FFT) = f \cdot \sqrt{\frac{1}{n}\sum_{i=1}^{n} \frac{\left(load_i^{exp} - load_i^{sim}\right)^2}{\|load^{exp}\|^2}} + (1-f) \cdot \sqrt{\frac{1}{m}\sum_{1=1}^{m} \frac{\left(FFT_i^{exp} - FFT_i^{sim}\right)^2}{\|FFT^{exp}\|^2}} \tag{3}$$

With $load^{exp}$ the load recorded by the sensor embedded in the lower die and FFT^{exp} the FFT deduced from that load signal.
And $load^{sim}$ the load obtained with the model and FFT^{sim} the FFT deduced from the modeled load. With f a balance weight for the load and the spectrum, f was chosen equal to 0.5.

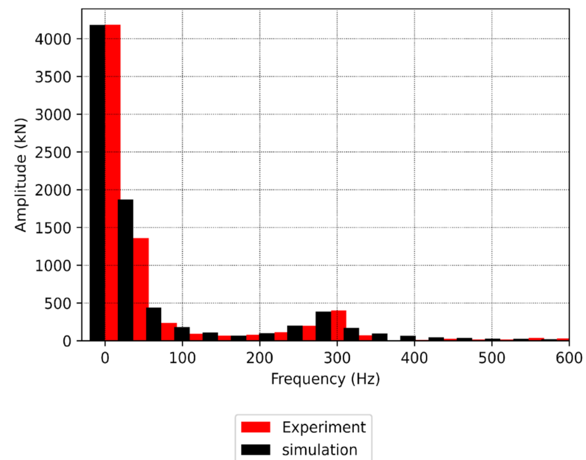
Results and Discussion
The load in function of the time, as well as the FFT, were plotted for the three different target functions and are compared to the experimental results (Fig. 3). For each function, the target value is also indicated. The three load curves obtained are significantly different, whereas the three FFT are very similar with the one coming from the experiments. Regarding the load curves, dephasing is observed in all curves as well as differences of amplitudes. As CF1 and CF2 have very closed definition (CF2 has just a square root more), results were expected to be similar, but this is not the case. The load curve for CF2 is singular compared to the ones for CF1 and CF3. For the experimental load curve, the load increase with important variations until reaching a peak, and after the load peak, the load decreases with smaller and smoother variations. CF1 and CF3 are following this trend, but this is not the case for CF2. This may be explained by the fact that the target functions may have found different local minimums.

Based on these results, the target function CF3 is chosen to perform a sensitivity analysis because it shows the best fit with the lowest target value.

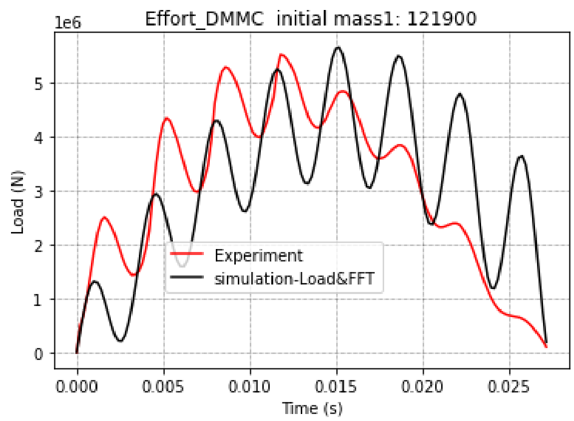
CF1



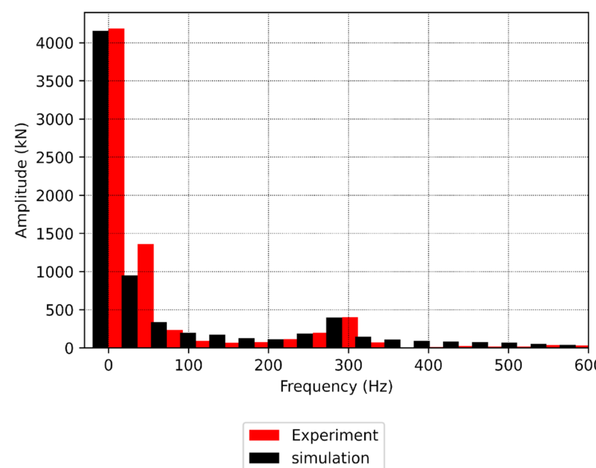
Target value: 4.68 $\times 10^{-3}$



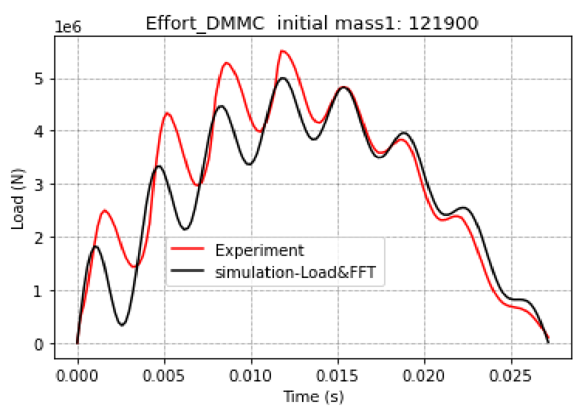
CF2



Target value: 1.29



CF3



Target value: 1.11 $\times 10^{-3}$

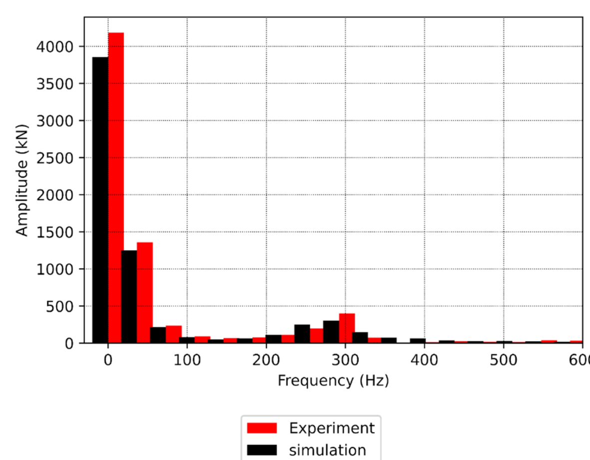


Fig. 3. a) comparison of experimental and simulated load signal for the 3 different target functions b) comparison of FFT on the experimental and simulated load signals for the 3 different target functions.

Sensitivity Analysis
To ensure the convergence of the algorithm to a minimum, a criterion on the target function variation is used and called *TolFun*. The minimization is stopped if, at the increment *i+1*, the equation is satisfied:

$$\frac{\left|CF3\ (load,FFT)_i - CF3\ (load,FFT)_{i+1}\right|}{\left|CF3\ (load,FFT)_i\right|} < TolFun \tag{4}$$

TolFun is obtained with a convergence study: the optimization is run with smaller and smaller values of *TolFun* and the identified parameters and target values of each *TolFun* values are compared (Table **1**). When the variation of these parameters is less than 1%, the *TolFun* value is considered to be adequate. There is no significant improvement of the target function or variation of identified parameters for *TolFun* values lower than 0.1. thus, *TolFun* will be set to 0.1.

Table 1. Target values and parameters values for different convergence criteria.

Convergence criterion	Fonction coût	m (kg)	c (N.s/m)	k (N/m)
1	1.5×10^{15}	3207	730117	2.07×10^{9}
1e-1	$\mathbf{1.1\times10^{-3}}$	**3192**	**360000**	$\mathbf{9.94\times10^{9}}$
1e-2	1.1×10^{-3}	3192	360000	9.94×10^{9}
1e-3	1.1×10^{-3}	3192	360000	9.94×10^{9}
1e-4	1.1×10^{-3}	3192	360000	9.94×10^{9}
1e-5	1.1×10^{-3}	3192	360000	9.94×10^{9}
1e-6	1.1×10^{-3}	3192	360000	9.94×10^{9}

Satisfying the equation (4) is not sufficient to ensure the convergence to a global minimum. The initial set of parameters can also have an impact on the solution find by the algorithm. The initial parameters are defined thanks to suppliers' documentations, when possible and a sensitivity study of the optimization on the initial parameters is conducted. For that, 50 new sets of initial parameters are generated by creating a +/- 10% perturbation according to a uniform law on the reference parameters. 46 optimizations are converging to the same target value with the same identified parameters, thus a global solution seems to be reached.

Then a sensitivity study of the optimization on the initial speed conditions is realized. 50 optimizations were run with 50 different values for the initial speed v_1 and v_2: the 50 different speed values were generated by creating a +/- 5% perturbation according to a uniform law on the reference speed values. Results are plotted (Fig. 4): 37 optimizations were converging to the same target value with 37 same sets of parameters identified.

The impact of the speed on the simulated load at k_{sensor} is also of interest. Thus, optimizations were run with +/-10% uncertainty error for the press input speed and the impact on the load was plotted (Fig. 5). Uncertainty error on the determination of the speed only affects the magnitude of the load with a relative deviation of 3.8%.

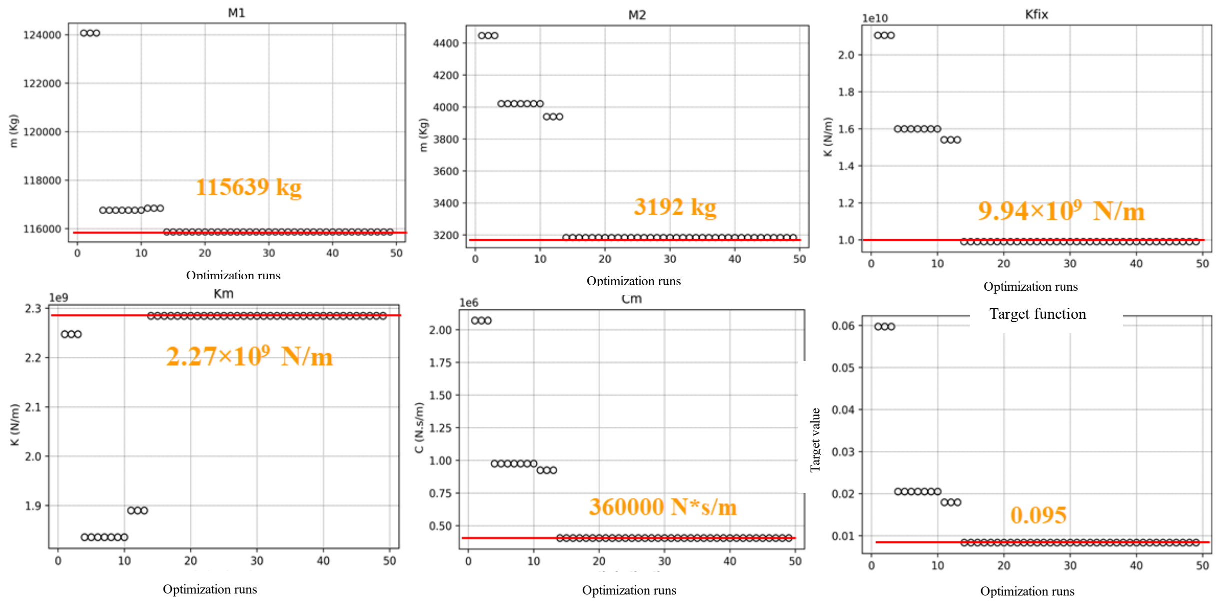


Fig. 4. Identified parameters values (m_1, m_2, K_{fixed}, K_{moving}, C_{moving}) and the target value for the 50 optimization runs with 5% uncertainties on the initial speed conditions.

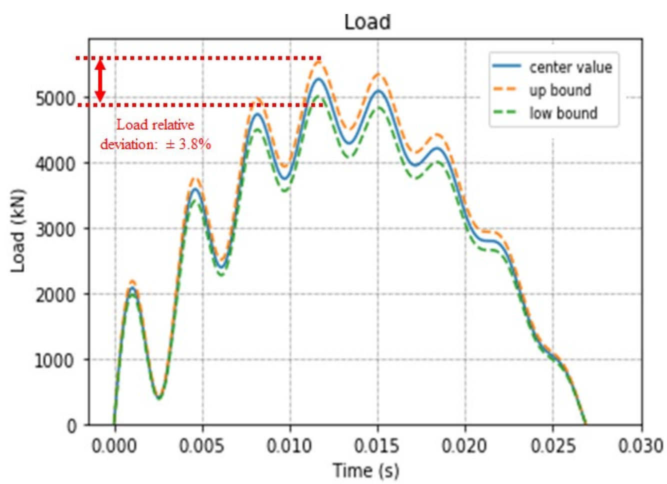


Fig. 5. Simulated load signal for the +/- 10% uncertainties on the initial speed conditions.

Finally, the impact of the parameters identification on the load simulated is also considered. For that, 10% uncertainty error was set for the identified parameters and the load response is plotted (Fig. 6). Uncertainty errors on the identified parameters induce a relative deviation of the load of 1.5% and affect both the load and the vibration mode.

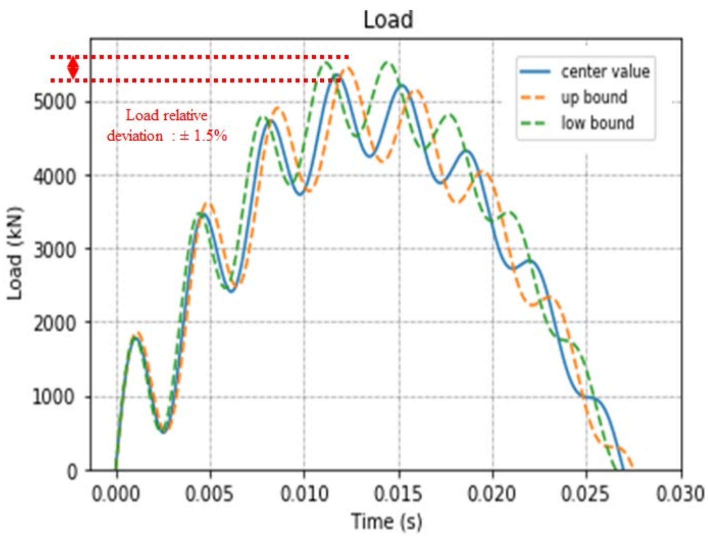


Fig. 6. Simulated load signal for the +/- 10 % uncertainties on the set of identified parameters.

Discussion

Concerning the parametrical identification, three different target functions were already tested and the one that seemed to be the best in terms of target values and load signal fitting was chosen. Despite these different tests, even more target functions could have been tested as well and the target function chosen could be different. The study can also be enlarged by testing different optimization algorithms to ensure that the global minimum is found. For instance, the target function integrates the load in function of the time and the FFT of that signal, but maybe the target function still can be improved by adding the ram displacement into consideration. Thus, the coefficient f of the target function could be revised, to give a different weight to each term.

Then, with the target function that was chosen, a sensitivity study of the algorithm on the initial set of parameters was conducted. The results converge; thus, it seems to indicate that a global minimum has been found. To ensure that fact, the study could be enlarged with a bigger perturbation on the initial set of parameters and with a higher number of optimizations.

The impact of the initial speed conditions on the parameters identified and the load simulated was considered. Concerning the parametric identification, results are converging, more than half of the sets of parameters identified are the same. Thus, the optimization is not significantly sensible to uncertainties on the ram speed. And the impact on the load simulated is lower than 4%, so it is negligible.

For the uncertainties on the identification of the set of parameters, it has an impact on the load's amplitude variation and on its dephasing. A relative deviation of 1.5% on the load amplitude was observed, thus remaining very low.

Summary

In this preliminary work on the parametric identification of a dynamic behavior model of a forging machine, one target function was chosen and a sensitivity study on the optimization was conducted. For the uncertainties ranges investigated, results are encouraging as they show a low sensitivity of the algorithm to perturbations on the initial conditions and on the initial set of parameters. But the study should be continued by testing other algorithms and larger ranges of uncertainties to ensure an accurate identification.

Furthermore, here the parametric identification is performed on a model of a press and its tools obtained thanks to bare strike, without billet. Thus, it could be interesting to validate the identified parameters on a case of a model integrating a blow on a billet.

Besides, the model presented here is valid for an entire production system including the press and its tools, but as several different tools can be installed on the same machine, it would be wise to dissociate the tools from the machine in such a dynamic model. And this would necessitate some changes in the target function's definition.

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