Artificial Neural Networks for Passive Safety Assessment

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***Abstract*—Nonlinear analysis has been applied to evaluate passive safety systems. It is based on the mechanical responses of the car structure and loads generated in the occupants as well as pedestrians. These responses are evaluated to design the car structure to manage and prevent the transmission of impact energy and as a passive element to absorb it and dissipate it. Human responses are evaluated through biomechanical assessment to identify and reduce human injury. Small electric cars have been introduced to reduce pollution, and although they have an environmental advantage, the battery can explode if the structure of the car body does not manage the deformation energy well. Due to their maximum velocity, the small electric cars can be introduced in some regions without analysing their crashworthiness behaviour. In this work, it is proposed to evaluate the nonlinear response of a mechanical bump shock absorber using a neural network, to predict its behaviour as an alternative tool to perform nonlinear initial evaluation, because there is human injury at low velocities. A combination of deceleration level and its time duration is necessary to evaluate the injury at low velocities. A dynamic neural network has been used to predict the deceleration, kinetic energy and deformation responses of a mechanical bump shock absorber. The methodology can be used by original equipment manufacturers, start-ups, suppliers and companies related to mobility and micro-mobility to perform safety assessments.**

***Index Terms*—Passive safety; crash; biomechanics; nonlinear analysis.**

I. Introduction

MOBILITY is designed to meet the requirements of production, design and manufacturability, and its mechanical strength, durability and passive safety must be analysed. The latter reduces the number of deaths and injuries in drivers, pedestrians, and cyclists involved in accidents [1]. The safety system has an impact on society not only for drivers and pedestrians [2] but also for some injuries requiring rehabilitation to recover mobility; in other cases, permanent damage occurs, so safety analysis is also important for the health sector, government and society. Evaluation can be performed through computer simulation or experimental tests. When improvements are developed with a simulation, it has the advantages such as running multiple scenarios with the same model or to obtain the dummy responses through interior behaviour where high speed cameras cannot cover. There are also some phenomena that cannot be modelled such as toxicity in airbags or some assumptions such as the crash test barrier being more rigid than real crash object.

The main component for passive safety is the car body. It has to be attractive for users but also has to meet mechanical requirements, such as strength, and contribute to weight reduction. This combines style development with the scientific approach to develop a creative body. After freezing the design, the mathematical model is generated with computer-aided design software. Every part has its own function, and loads are static and dynamically concentrated in door hinges and latches, which are generated by braking, acceleration or body torsion for lateral movements. Thin-walled structures are used in automotive, marine, aircraft due to their capability to absorb energy, minimizing the transmissions to occupants [3], and dissipate kinetic energy through plastic deformation [4], [5], [6], [7]. To define how to manage the energy, the body car is split into walls: body side, roof, firewall, front frame, rear frame and compartment floor [8].

The roof assembly main function is in the case of roll over to prevent hard contact in passenger ejection. Rollover and nearside impact collisions have the highest percentages of partial ejection, which can result in soft tissue injuries [9]. The front frame is the assembly from the bumpers until the firewall. This frame is the compartment of the powertrain, suspension links, and steering box. To reach compliance, the front-end structures have to reduce the acceleration (10-30g) and minimize intrusion to the passenger compartment [10], [11]. Together with the body side and floor, it minimizes injury to pedestrians. The rear frame main loads are dynamic seat and belt loads, and the main challenge in addition to managing rear crashes is to prevent resonances with the body frame [12]. High acceleration during the crash leads to internal injuries (bone fractures and organ ruptures) accompanied by severe bleeding. The human body collision with interior parts of the vehicle, such as the steering wheel, the results in external injuries, which can be fatal, serious or non-incapacitating [13]. Occupant safety in a side-impact crash is usually evaluated by measuring the peak acceleration of a passenger's pelvis and chest areas with the aid of instrumented test dummies. Thoracic injury can be attained due to the impact or result of the mechanism of airbag inflation [14]. Thorax compression in combination with hyperextension of the neck can result in laceration of the aorta [15], [16]. Impact effects are also evaluated for pedestrians because they are not protected by any structure [17]. Possible fractures due to impact to the knee are fractures (acetabular, patellar, femur), dislocation of knee muscles, damage to tendons and femur injury [18]. The interlayer of the windshield improves the crash protection of pedestrians and passengers [19]. Restraint mechanisms play an important role in paediatric users, such as Lower Anchors and Tethers for Children (LATCH) [20], and anchor wheelchairs can transmit forces to the floor of up to 30 kN [21], [22].

Safety assessment is also important in micro-mobility such as electric bicycles (e-bikes); despite the use of helmets, electric scooters have increased the probability of human injury in crash events [23]. Brain injuries can incur from

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impact between the rider with the windshield or with the ground [19]. The causes of crashes are loss of balance, evasive action, railways track or slippery roads [24]. Small and mini-electric cars are smaller than conventional cars . The average range of mini-EVs is approximately 100 km, with a maximum speed ranging from 40 to 60 km/h [25]. Electric vehicle deformation can be minimized when the structural parts are strengthened to reach crashworthiness requirements [26], [27], and battery cells can be subjected to impact and vibrations [28], [29]. Rechargeable energy storage systems such as lithium-ion batteries bring safety risks in the event of a collision [30], [31]. While more energy stored in the battery pack of an EV translates to a longer range, the downside is that accidents are more violent due to inevitable battery explosion [32]. The rear collision of vehicle battery packs is more dangerous. The mechanical properties and failure mechanisms of the battery separators play a crucial role in the integrity of lithium-ion batteries during an electric vehicle crash event [33]. To make the electric car structure safer [34], it is proposed to place the battery pack into the secondary safe zone of a unibody-type vehicle instead of on the floor.

It is important to evaluate the nonlinear responses of impacts in any vehicle because injuries can be permanent or require rehabilitation, impacting society. In this work, an analysis using a neural network is proposed to validate this proposal. The response of the mechanical bump shock absorber to three responses is analysed: deceleration, kinetic energy and deformation energy, which has an average error of less than 1%. In the case of deceleration and kinetic energy, only the time was used as an input, and these signals were the target. In the case of the deformation energy, the time, deceleration and kinetic energy were used as inputs. The evaluation of the prediction was only after the first contact, before that point it has structural noise generated by the movement in the simulation.

This paper is organized as follows. Section 2 describes the importance of safety systems to reduce injuries and reviews the main biomechanical responses to assess injuries. Section 3 introduces the dynamic artificial neural network used throughout this paper. Section 4 describes the nonlinear finite element analysis performed to obtain the time series responses. Section 5 then combines the time history results from the finite element analysis with the ANN prediction. Section 6 presents our conclusions.

II. Safety Systems.

Original equipment manufacturers have been developing better structural designs to reduce injuries to occupants and pedestrians in accidents. Crashworthiness combines the structural response of the vehicle (car, trains, helicopters, airplanes) and biomechanics of occupants as well as pedestrians [35], [36], [37]. Humans are exposed to mechanical loads coming from physiological processes inside the body for organs and tissues, not only from the impact of restraint systems [38]. The vehicles developed have to meet the requirements and regulations for the New Car Assessment Program (NCAP). Depending on the type of impact, different parts of the body are analysed. Figure 1 shows different scenarios that are analysed to evaluate safety performance.

The values for which to perform some impact simulation tests are defined based on time windows known as corridors, as shown in Figure 3 [39], which are obtained based on experimental crash measurements. The main scope is to evaluate the probability of injury.

Injury criteria are an important tool to evaluate the severity developed in an accident, and they correlate the physical parameters (force, acceleration, moments) with the probability of injuring a specific body region. The most common code used to evaluate crash response is the Abbreviated Injury Scale (AIS), which is based on injuries from traffic accidents [40], [41]. Human variables such as age and psychological and physical features change injury severity [42], [43]. Models used in trauma biomechanics include anthropomorphic test devices and physical and mathematical models. The kind of dummy also depends on the crash type; it can be full-scale testing (rollover test, frontal and lateral impact), sled testing and different impactors used in pedestrian safety testing of the front of a car. The roof is related to the head impact protection for interiors. Free motion headform FMH is used to evaluate the compliance and the energy dissipation in the vehicle interior. To evaluate its response, a headform is impacted to specific targets as pillars, and the side rail and the front header reach velocities 23.6 km/h, measuring the head injury criterion HIC, which is also evaluated in motorcycle collision [3]. It is described as

$$HIC = max\left\{\left[\frac{1}{t_2 - t_1}\int_{t_2}^{t_1} a(t)dt)\right]^{2.5}(t_2 - t_1)\right\} \quad (1)$$

Improvements to vehicle frontal crashworthiness have led to reductions in toe pan and instrument panel intrusions [44], [14]. Hollow abdominal organ injury is a universal problem in frontal collisions, and the initial lap belt position may play a greater role in the occurrence of these injuries. Pretensioners, which apply a force to the lap belt early in the collision event to remove initial slack, are only capable of pulling the belt along a fixed angle. They are not yet capable of dynamically changing the angle of the belt or the position of the belt relative to the pelvis. To prevent it, anti-submarining technologies have been proposed [45]. Transfer functions can be evaluated to reduce the human injuries, it can be attained using active systems to improve the vehicle performance. While it can be used to tuned the suspension displacement using weighting matrices [46], nonlinearity can lead to system instability [47], [48]. Dummy chest acceleration can be reduced by decreasing door velocity during impact and employing a side airbag, while pelvic acceleration can be reduced by reducing door crush, decreasing wheelbase, and having a soft or breakaway centre console. A rigid centre console traps the pelvis, loading the side opposite the intruding door and increasing the frequency of pelvic fractures for a given amount of door crush. Stiffening doors does reduce door intrusion and door velocity but at a penalty of greater vehicle weight and side acceleration. Padding, such as a thoracic airbag, reduces chest accelerations but only by a relatively small amount [49].

III. Crashworthiness Assessment.

While structural damage is managed based on strengthened designs, lightweight design is desired. Thin-walled

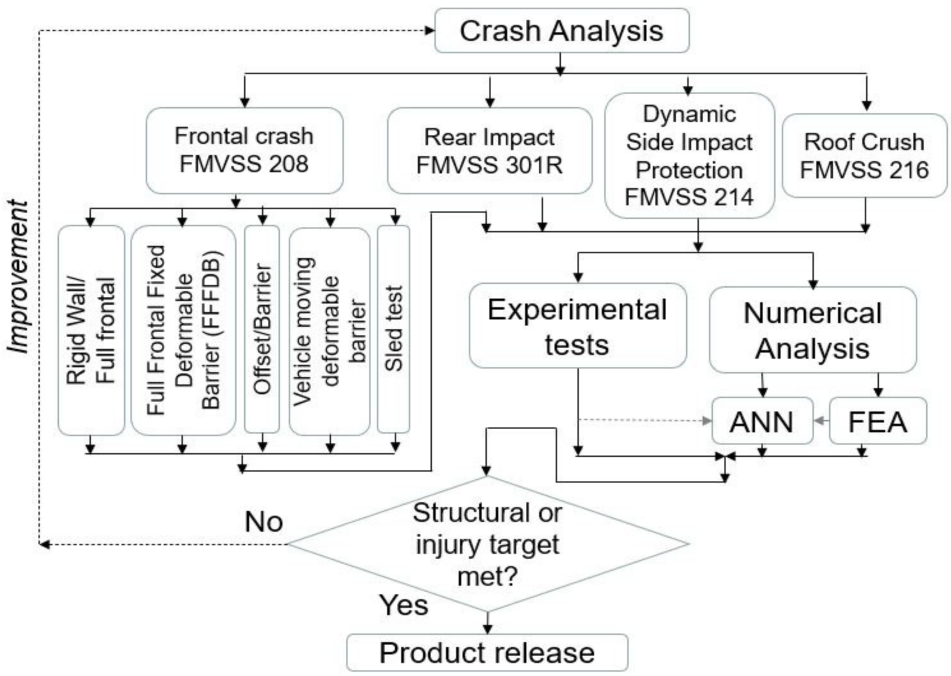

Fig. 1: General overview for crash analysis.

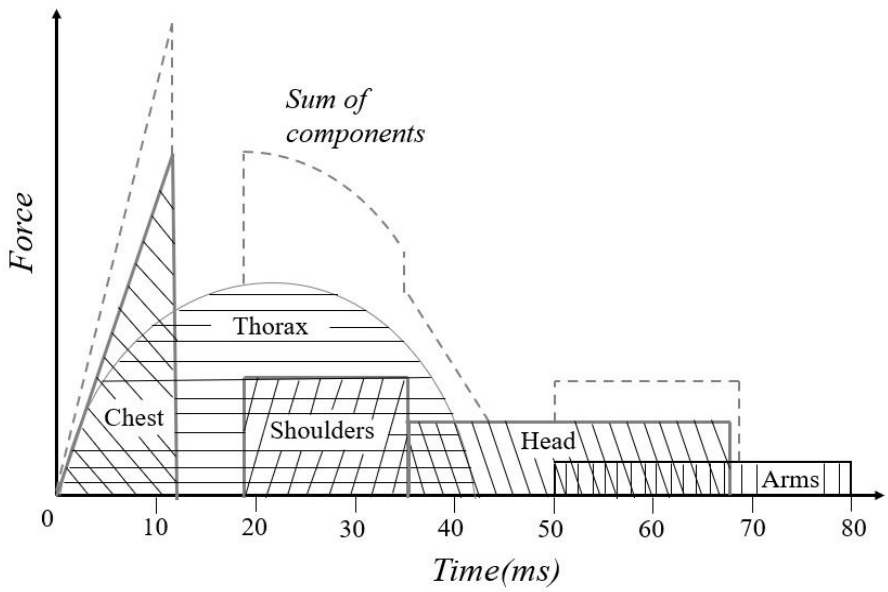

Fig. 2: Schematic Force-time crash corridors.

components have been used to dissipate energy by progressive folding. It is using different materials or design topologies, some proposals are reproducing cells as honeycomb structures. It can do it only using the deformation energy of the component or using a sacrificial extrusion by axial cutting to reduce load fluctuations, its mean crush force can be expressed as:

$$P_m = \frac{2\sigma_o \sqrt{(\pi t)}^3 r_m}{\sqrt[4]{3}\left(0.86 - 0.37\sqrt{t/r_m}\right)} \tag{2}$$

Where σ_o is the Flow stress of extrusion material [50].

Honeycomb structures are used in various industrial applications as shock absorbers in airplanes and high-speed trains for energy absorption during crush transforming the impact energy into plastic strain its capability to absorb energy is influenced by the material, thickness, and geometric parameters of a honeycomb cell [51]. The buckling load is evaluated as a function of the wall and cell size:

$$P_{crit} = \frac{K E_s t^3}{(1 - \nu_s^2)\, l} \tag{3}$$

For the honeycomb an important parameter is the foil thickness (t) as is expressed by crush strength:

$$\sigma_m = 6.63\sigma_o \left(\frac{t}{D}\right)^{5/3} \tag{4}$$

Normal collapse stress of the honeycomb in the out-of-plane direction σ is expressed by:

TABLE I: Crashworthiness parameters.

Parameter	Model
Total energy absorption	$TEA = \int P_i dS$
Specific Energy Absorption	$SEA = \frac{\int P_i dS}{m}$
Crush Force Efficiency	$CFE = \frac{P_{av}}{P_m}$
Energy absorbing effectiveness factor	$\psi = \frac{3GV_o^2}{8\sigma_o A\delta_f\varepsilon_r}$

$$\sigma = 4.26cos^2\left(\alpha - \pi/2\right)\left(1 + sin\left(\alpha - \pi/2\right)\right)^2 E_s\left(\frac{\rho}{\rho_s}\right)^3 \tag{5}$$

where ρ_s is the density of the solid cell wall material [52].

The design topology energy absorption is evaluated with the parameters of Total energy absorption TEA, that is the area under the load-displacement curve; Specific Energy Absorption SEA, that is is the energy absorbed per unit mass; Crush Force Efficiency CFE, Is the relationship between the crushing load P_{av} and its maximum value P_{max}; Energy absorbing effectiveness factor, that Is the relation of the total energy that can be absorbed in a system to the maximum energy up to failure in a traction test; as are shown in Table I.

IV. Artificial Neural Network

By its nature, an artificial neural network has been implemented to solve nonlinear phenomena and to predict their behaviour. NNs can be used to forecast traffic flow and analyse highway safety [53] or in complex problems such as hot stamping [54], [55]. Before, during and after the impact event, there are factors related to the car, driver, pedestrian, traffic flows, and highway variables [56]. Using long short-term memory (LSTM) recurrent neural networks, individual drivers are identified based on their pattern of acceleration-deceleration and exceeding the speed limit [57], and the results can be used to improve the mechanical behaviour of the car structure or to generate predictive models using machine learning [58]. The lateral load transfer to roll stability control is estimated using a neural network [59]. [60] includes the evaluation of eye and environment data in addition to the vehicle information. This is also important because previous accident generates speed reduction and rubbernecking, which increases the probability of secondary crashes [61]. A real-time crash prediction model using a deep learning method called a deep convolutional generative adversarial network (DCGAN) is used to analyse traffic safety proactively to reduce crash risk [62]. A fusion convolutional neural network with random term (FCNN-R) model is proposed for driver injury severity analysis [63]. [64] proposed a neural network to reproduce car kinematics during a collision using a nonlinear autoregressive model to predict the kinematic responses (acceleration, velocity, and displacement) during a collision. An ANN can be used to analyse the specific energy absorption [65]. Accident modelling requires the modelling of the impact, which in turn requires the estimation of the deformation energy [66]. A feed forward neural network has been implemented to predict the fracture of the car body and to predict crash-injury outcomes [67]. [68] introduces an approach to pre-crash velocity determination based on artificial neural networks taking into account the displacements on the front end. The initial velocity and structural characteristics of any vehicle are the main factors affecting the vehicle response in the case of frontal impact. Recurrent NN can be used to predict the nonlinear relationships in crash responses [69]. The crashworthiness performances of square thin-walled tubes are investigated under axial impact loading by using an artificial neural network [70].

The series–parallel structure of nonlinear autoregressive exogenous $(NARX)$ models is used for dynamic systems for fault detection, forecasting wind speed and power in wind turbine blades, failures in gearboxes, bearings [71], and a functionally graded thickness pillar characterized by a thicker wall thickness to absorb energy [72]. The RBF-NARX neural network has neurons based on radial functions. In the process of identifying this network, the neuron's number in the hidden layers is increased, and the parameters are adjusted to minimize the output error of the model. The generalized regression neural network GRNN-NARX model consists of neurons with radial functions and has a feed-forward structure that uses a relatively non-repetitive and straightforward algorithm for training [73]. Since most of the systems around us exhibit some form of nonlinear behaviour, nonlinear system identification techniques are tools that help us gain a better understanding of our surroundings and potentially let us improve their performance.

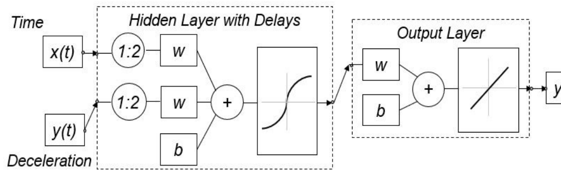

Fig. 3: Schematic diagram of an NARX neural network.

A $NARX - NN$ approach is described conceptually by:

$$y(t) = f\left[y(t-1), ..., y(t-n_y), u(t-1), ...u(t-n_u) + e(t)\right] \tag{6}$$

where f is an unknown static nonlinear mapping; t is the discrete-time index; $u(t)$, $y(t)$ and $e(t)$ are the input, output and equation error, respectively; and u_n and n_y are the number of past input and output terms, respectively, [74]. Noise is assumed to be distributed as random variable with a normal distribution. Figure 3 shows a schematic representation of the $NARX - NN$ architecture [75]. This architecture has input, hidden and output layers. The input layer is denoted by the time delay units $(z-1)$, which are the past samples required by the model to predict the response. The hidden layer is composed of a finite number of neurons to map the relationship between the set of input data and the corresponding output data, expressed as

$$y_p(t) = f_1\left(\sum_{i=1}^{K} I_{W_i} u_i + \sum_{j=1}^{K} I_{W_o} y_j + b_i\right) \tag{7}$$

where f_1 is the bipolar sigmoid function, I_{W_i} and I_{W_o} are the connection weights for u and y, respectively; K is the number of neurons in the hidden layer; and b_i is the bias.

The bipolar sigmoid function (f_1) improves the convergence of the training algorithm and is defined as

$$f_1 = \frac{2}{1+e^{-2k}} - 1 \tag{8}$$

where k is the value of the inside of the parenthesis in Eq. 5. f_1 is used to compute the model output, $\hat{y}(t)$ as

$$\hat{y}(t) = \sum_{i=1}^{K} O_{W_i} f_1 + b_2 \tag{9}$$

O_{W_i} represents the connection weights of links connecting the nodes in the hidden layer to the output node, and b2 is the bias term. Note that a training algorithm must be used to find the values of I_{W_i}, I_{W_o}, O_{W_i}, b_1 and b_2. All the weights used by the network are placed in a weight vector w, defined as

$$w = [I_{W_i} I_{W_o} O_{W_i}] \tag{10}$$

In this work, Bayesian regularization (BR) is proposed for the training algorithm in the NARX model. The topology of the dynamic neural network includes 44 hidden neurons and 2 delays. Seventy percent of the samples were organized for training, and 15% were organized for validation and testing.

V. Finite Element Analysis

To obtain the energy absorption time history, the nonlinear response of the mechanical bump shock absorber is simulated, as shown in Figure 4. An aluminium honeycomb panel is used as the deformable body. A nonlinear finite element simulation using Abaqus Explicit V6.8-2 was performed to simulate the bump shock absorber. Normal contacts are defined between the rod and the front plate; the front plate and the honeycomb panel; and the back plate and the honeycomb panel. Normal and tangential contacts are defined between the guides and the plates using a friction coefficient of 0.09.

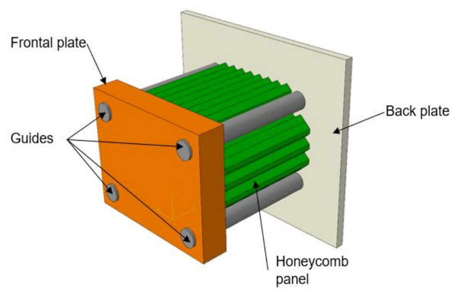

Fig. 4: Mechanical bump shock absorber.

Figure 5 shows the model used. The finite element model has a mesh size of 5 mm.

The rod cannot rotate in any direction, and the translations are restricted in the y and z directions. A velocity of 15,555.5 mm/s is applied to the bump shock absorber in the x direction, as shown in Figure 6.

The finite element simulation of the bump shock absorber at different times is shown in Figure 7. The bump shock absorber approaches the decelerator rod (Figure 7a). At 9 ms, the bump shock absorber is almost in contact with the decelerator rod (Figure 7b). Then, the yielding of the aluminium honeycomb panel is reached, thus starting plastic deformation (Figures 7c-7d).

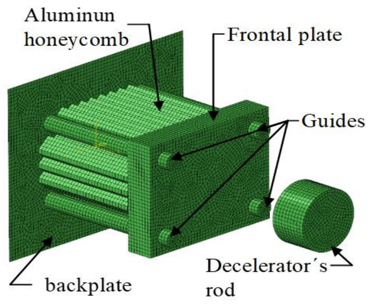

Fig. 5: Model used in finite element simulation.

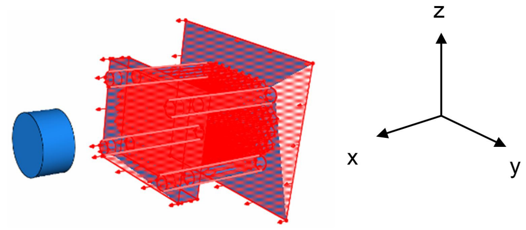

Fig. 6: Velocity of the Finite element model.

VI. Results and Discussion

Figure 8 shows the filtered and unfiltered acceleration data, which were analysed and edited using a CFC60 100 Hz low-pass filter. The filtered response shown in Figure 8 is used as input for the ANN, and the results are shown in Figure 9.

To evaluate the feasibility of predicting nonlinearity, the analysis was split into three evaluations: the first evaluation was deceleration, and the second evaluation was kinetic energy, as shown in Figures 9a and 9b. The average errors were 0.67% and 0.0002%, respectively. For deformation energy, two topologies were evaluated: ANN1 has the response by itself, while in ANN2, the deceleration and kinetic energy were also included; both predictions are shown in Figure 9c.

Although ANN2 shows some peaks at approximately 0.0147, 0.0163, 0.0171 and 0.0181 s, the prediction is better than that of ANN1. This slope increases with a delay of 0.0001 s, and at 0.0103, the delay is not only in time but also in amplitude. Including the deceleration and kinetic energy helps to predict the deformation energy, reaching a prediction error average of 0.612%. This result proved that the dynamic neural network can be used to predict nonlinear behaviour. This analysis was based on the structural response of the mechanical bump shock absorber. It can be extended to analyse biomechanical responses because it includes measurements of acceleration, force, and moments at different body positions.

VII. Conclusion

In this study, the mechanical bump shock absorber was analysed to predict its energy absorption. Normally evaluated with experimental tests or with finite element analysis, this proposal uses an ANN. A nonlinear analysis using finite element analysis has high computational requirements, and the aim of this work is to develop an alternative way to analyse the structural response and biomechanical behaviour in different crash scenarios to reduce the social health impact with permanent lesions or extensive and expensive rehabilitation. Based on a literature review, crashworthiness

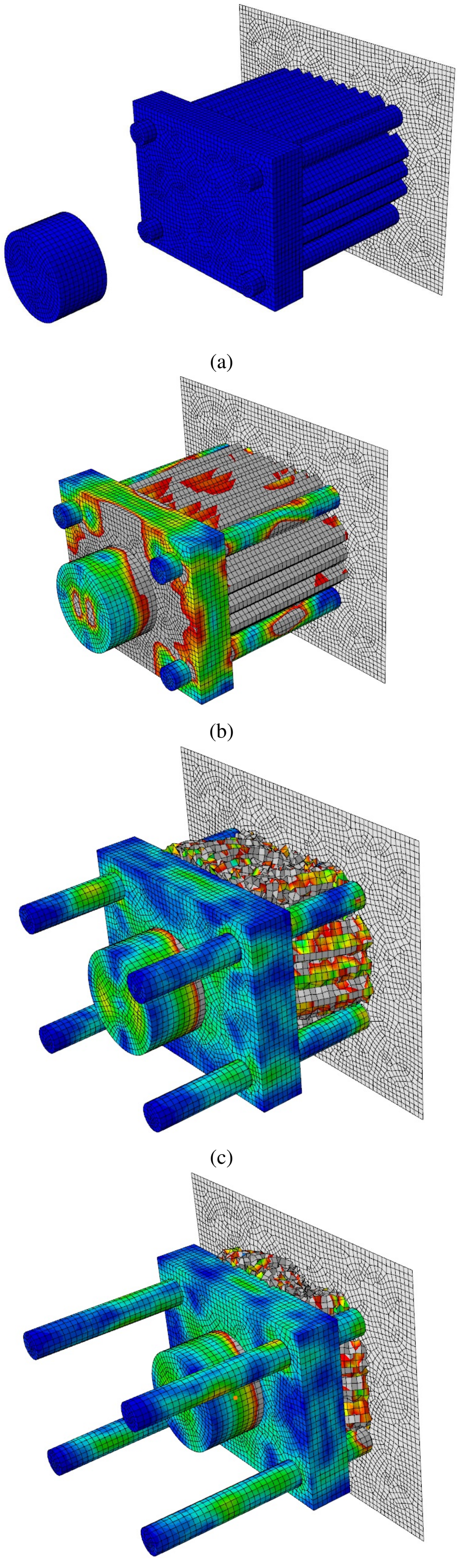

Fig. 7: Simulation results of the bump shock absorber. (a) 0 ms, (b) 10 ms, (c) 15 ms and (d) 20 ms

analysis is necessary to develop regulations at low velocities to include micro-mobility to reduce injuries. ANN can be used to predict the most critical crash scenario for a specific vehicle and can then be evaluated by FEA and experimental tests. There are two ways to obtain the information to train and validate the networks, from experimental tests or from numerical simulations. Integrating an ANN to predict nonlinear responses can be used to analyse different scenarios one at the time. It reduces the time of analysis and can improve the assessment. It is important to validate the results; based on this fact, the prediction cannot be extrapolated to other velocities or other component characteristics with different stiffnesses. There are some factors that are not included in the finite element analysis, such as toxicity in the airbag. Therefore, it is necessary to develop mathematical models that predict different scenarios to include external factors in the ANN, such as age or some other specific human characteristics. It is also necessary to establish not only the signals as output but also generate directly the injury assessment. Extensive network training is required to accomplish this.

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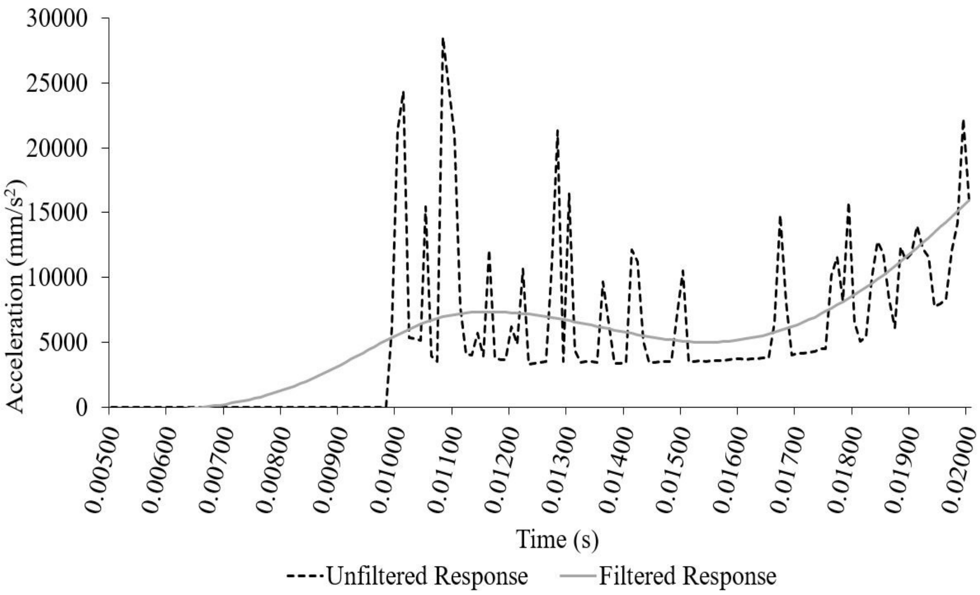

Fig. 8: Filtered and unfiltered deceleration history.

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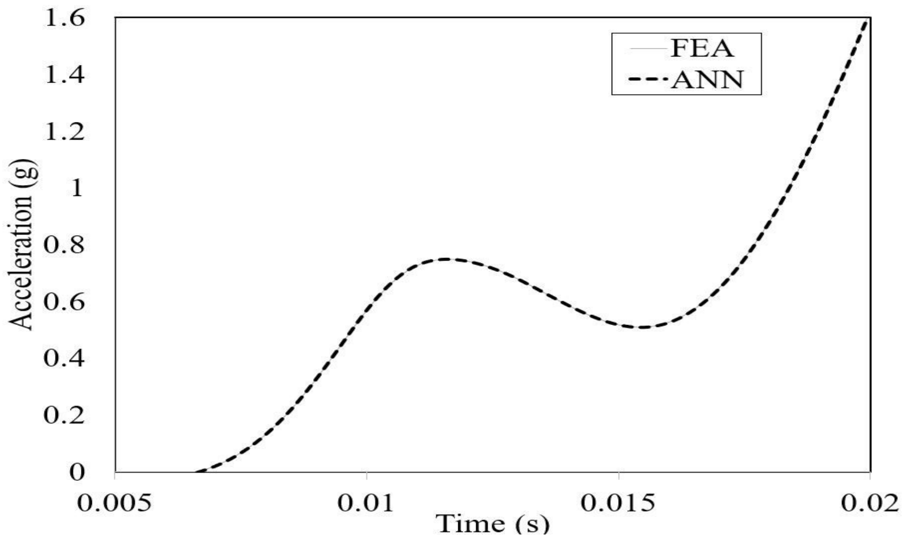
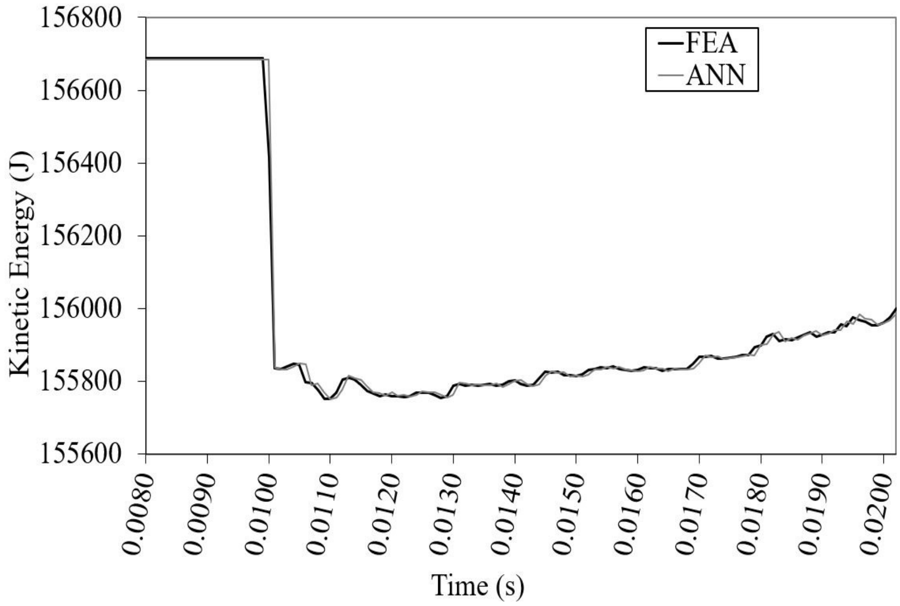


(a)



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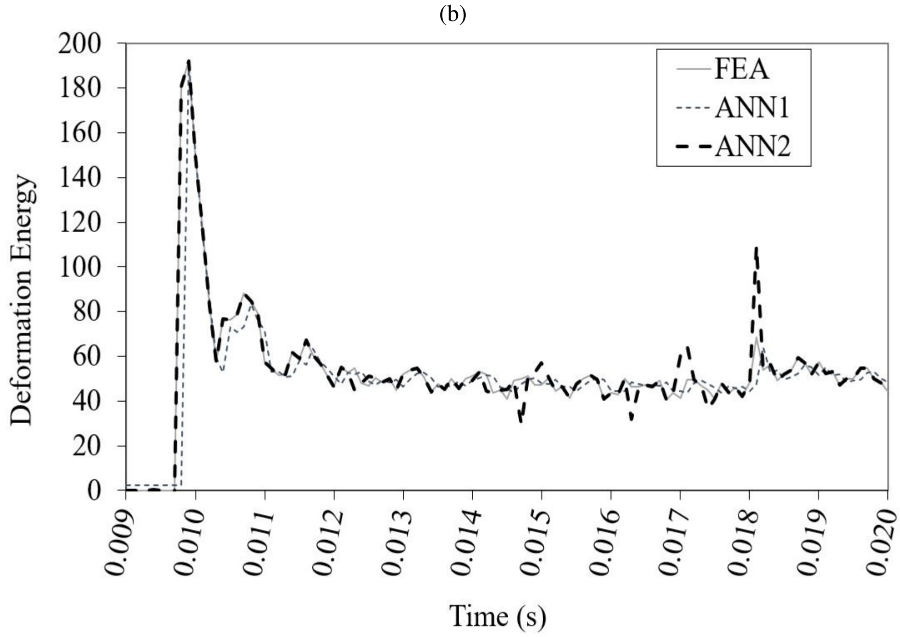

(c)

Fig. 9: Evaluation of the results of (a) deceleration, (b) kinetic energy and (c) deformation energy

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