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Please cite this paper as:
Naser M.Z. (2019). "Enabling cognitive and autonomous infrastructure in extreme events through computer vision." *Innovative Infrastructure Solutions*. https://doi.org/10.1007/s41062-020-00351-6.

Enabling Cognitive and Autonomous Infrastructure in Extreme Events through Computer Vision

ABSTRACT
As advent by the continuous inertia towards integrating artificial intelligence into daily operations, it is a matter of time before artificial intelligence reforms the field of structural engineering. From this point of view, this paper explores how computer vision and deep learning can be applied, in combination with advanced finite element analysis, to realize cognitive (self-diagnosing) and autonomous infrastructure. The outcome of this study demonstrates that computer vision not only can enable a structure to understand that it is undergoing an extreme event but can also allow it to trace its own performance and to independently respond to mitigate prominent failure/collapse. Findings of this work infer that computer vision can serve as an intelligent, and scalable agent to accurately trace structural response, identify different damage mechanisms and propose suitable repair strategies whether during or in the aftermath of a traumatic event (i.e. fire, earthquake). Finally, a series of challenges and future research directions are outlined towards the end of this paper.

Keywords: autonomous and cognitive infrastructure; computer vision; deep learning; fire; earthquake.

INTRODUCTION
Civil infrastructure are primarily designed to serve occupants and commuters over an extended period of time that often exceeds 25-50 years [1]. As a result of this prolonged service life, and given the tendency of structures to age, civil constructions become vulnerable to the increasing frequency and intensity of natural and manmade extreme events (i.e. earthquake, terrorist attacks etc.). As such, recent research efforts have been directed toward developing practical strategies to enhance the resilience of critical infrastructure [2]. Most of these strategies rely on classical solutions in which the primary objectives are to: 1) enhance properties of construction materials, 2) improve the design of new load-bearing structural systems or, 3) upgrade or strengthen existing structural components to withstand intense loading conditions [3–5].

A revolutionary look into the near future shows that it is possible to realize resilient infrastructure that can adapt to a wide variety of loading conditions. This can be achieved by leveraging recent advancements in design and computing [6–8]. In such a view, a new generation of infrastructure with highly adaptive load-bearing systems can allow a structure to autonomously reconfigure its layout in order to adapt and respond to extreme loading conditions. This concept allows a structure not only to comprehend that it is undergoing a severe loading event (as well as the magnitude of such event), but also enables it to trace its own performance during such event and to independently respond to mitigate prominent failure/collapse. In order to achieve such high level of structural awareness, appropriate frameworks utilizing different fields of computer science, sensing and structural engineering need to properly converge.

Such a framework could be realized through AI which has become the focal point of research in the past two decades. While the application of AI into the field of structural engineering is fairly

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lagging [9–15], the application of contemporary AI-based algorithms, i.e. Deep Learning (DL), Pattern Recognition (PR), Genetic Programming (GP) etc., continues to rise [16–18].
In lieu of the above algorithms, CV is a high profile technique that can be broadly defined as the operation of how computing devices are capable of developing a high level of perception from abstracts, images or videos as to automate tasks often carried out by humans [19]. In other words, CV is the ability of a computing workstation to comprehend, identify, detect, or classify visuals with minimum to no human intervention. From this paper's point of view, CV is applied through specialized forms of artificial neural networks (ANNs). Some of the commonly used ANNs include; Region-based Convolutional Neural Network (R-CNN), Region-based Fully Convolutional Net (R-FCN), Single-Shot Detector (SSD) etc. While these derivatives share some features in common, they still differ on a number of fronts; primarily due to the nature of their development and intended use [20–22]. It should be noted that a more in-depth review on other architectures such as You Only Look Once (YOLO) and Visual Geometry Group (VGG) can be found elsewhere [23,24].

A deeper look into the published literature shows that a common feature between current efforts can be summed by primarily applying AI and CV to investigate: 1) traditional phenomena where a good amount of knowledge (experimentations) exists [25], and 2) phenomena occurring at ambient conditions (i.e. thermal comfort etc.) [26]. This observation was also reported in notable reviews such as those carried out by Sohn [27], Simoen et al. [28] and Xie et al. [29]. This infers that the application of AI towards extreme loading conditions continues to be limited mostly due to the restricted availability of raw data points that can be used to train CV-based models; given the lack of testing facilities and instrumentations that can endure harsh loading conditions (i.e. fire, earthquake etc.).

With the hope of bridging this knowledge gap, this work presents a novel framework designed to comprehend structural behavior during (or in the aftermath of) an extreme event. Rather than applying traditional assessment techniques such as manned or unmanned visual inspection [30] etc., a CV-powered assessment tool is developed using DL to examine the performance of structural components (i.e. composite steel girders and fiber reinforced polymer (FRP) strengthened reinforced concrete beams) under fire and earthquake loading. With the aim of providing a sound and consistent collection of raw data points (i.e. imagery), actual full scale fire and seismic tests are first utilized to develop a highly complex and three-dimensional finite element (FE) model capable of accurately tracing the complete response of fire-exposed and earthquake-subjected structural components. These models are then used to generate a realistic imagery database of damage response similar to that observed in full scale tests. The FE-based imagery is then used to train, validate and also test the accuracy of a developed CV tool. The same imagery is also used to train the tool to arrive at suitable repair strategies as to salvage event-damaged structural members. The presented results show that the developed methodology can facilitate safe inspections and timely repairs. Finally, a discussion on the scalability of the proposed concepts to full-sized structures, as well as associated limitations and current challenges is outlined towards the end of this paper.

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A FRAMEWORK TOWARDS ASSESSING STRUCTURAL RESPONSE UNDER EXTREME LOADING CONDITIONS

Proposed framework

The proposed framework comprises of seven steps as outlined in Fig. 1. The *first* step starts by collecting imagery on damaged structural members as to compile a database. This database is to contain images (or videos) on various structural components (i.e. beams, columns, walls etc.) of different configurations (e.g. construction materials, restraint conditions, loading levels, functionality etc.). Such rich database can then be used to train and develop a CV-based model as part of the *second* step. In this step the database is split into three sets for training, validating, and testing purposes. The training of the CV model often follows an iterative procedure until a satisfactory performance is achieved [19]. Both of these steps are part of the development stage in the proposed framework.

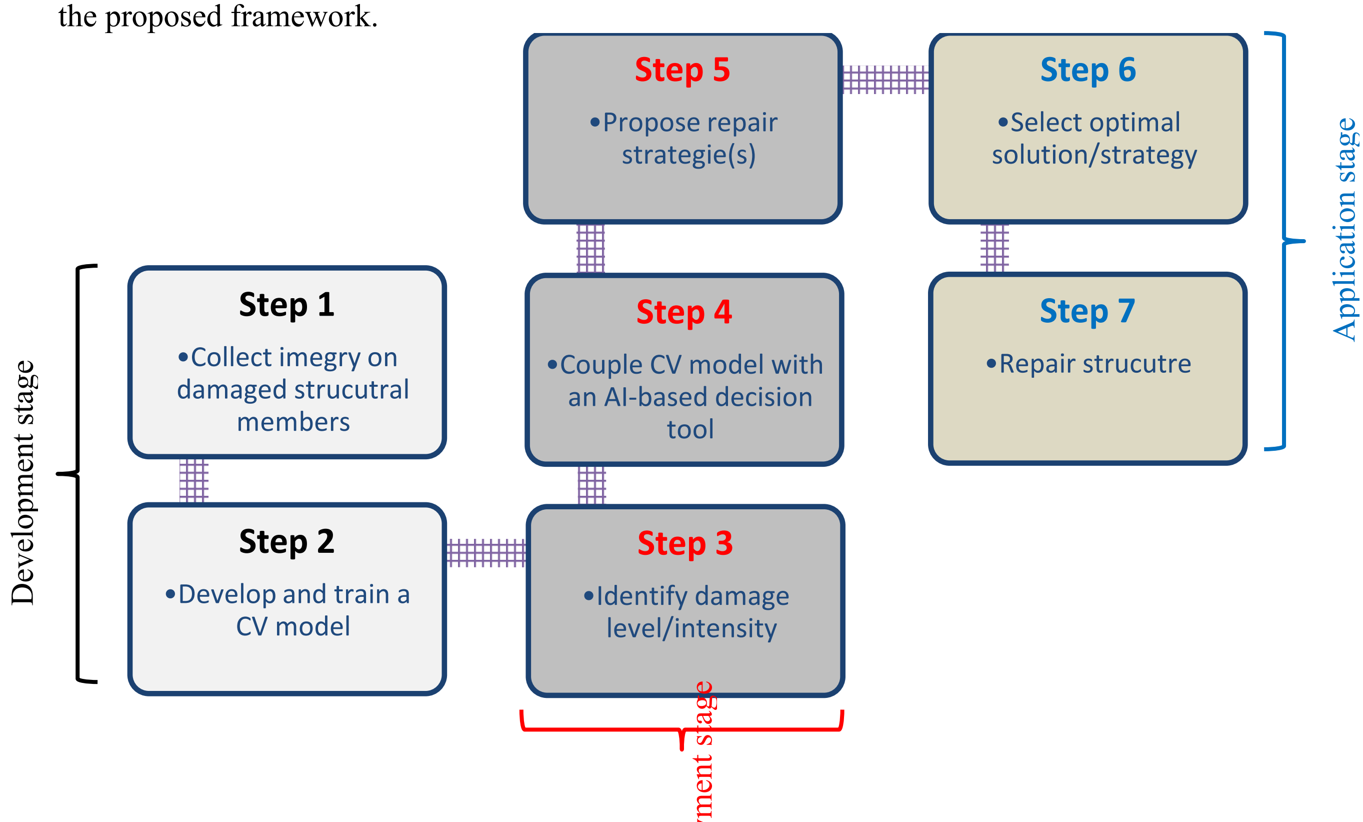

Fig. 1 Framework for structural assessment using CV (please note that "Development stage", "Deployment stage" and "Application stage" are covered in the second, third and four sections, respectively.

Then, the properly trained CV model is deployed in the deployment stage to examine a damaged member (say a concrete beam) and this takes place in the *third* step. In this step, the CV model can be used to: 1) passively assess the state of a structural member after being damaged (i.e. once a fire is extinguished or post a seismic incident) through imagery collected by means of traditional inspection tools or those mounted on unmanned vehicles such as drones etc., or 2) dynamically trace structural performance through embedded visual sensors during an event i.e. throughout a fire incident (and both of these scenarios will be highlighted in later section). The result of the CV analysis obtained from the third step is input into step *four* which couples the identified level damage to a DL-based decision tool. This tool further analyzes the outcome of the third step and compares it against prior (or similar) documented incidents and applied repair solutions at the time of previous incidents. A solution (or a series of solutions) is then proposed to retrofit such damage in the *fifth* step.

The application stage is the final stage in the proposed framework and comprises of two additional steps. In the *sixth* step an optimal solution strategy is selected primarily based on the CV tool coupled with knowledge/experience of practicing engineer(s). Incorporating a human-based knowledge system is important in the case where the developed CV-based decision tool is not supplemented with a library of properly documented structural failures. This added knowledge system can support the CV-based tool to provide and verify the applicability of the proposed repair solutions. The *seventh* and final step is to apply the selected repair strategy in order to repair the damaged structure.

When fully functional, the proposed tool has the potential to be applied and integrated into an autonomous and cognitive infrastructure through sensors and embedded cameras as described in a previous studies [7,31]. The main use of this tool is to identify the point in time when main structural members become vulnerable to failure (collapse) and hence activates autonomous structural components (ASCs); which are secondary and redundant load-bearing systems to facilitate redistributing portions of the applied loading toward non-damaged components [7]. An illustration of an ASC is shown in Fig. 2 where the strength of the beam (in red) is degrading due to the effect of heat arising from a fire incident. With prolong exposure to elevated temperatures, the beam further deteriorates. This jeopardizes the structural integrity of the structure as excessive deflection can trigger failure of the ceiling and partial/complete collapse of the structure. Once the cognitive and autonomous infrastructure identifies that such failure is eminent, the structure releases an ASC that is pre-integrated into compartment boundaries to: 1) limit deflection of the fire-damaged beam, and 2) redistribute loadings applied to the beams to the slab to minimize possibility of overstressing the beam and probability of collapse (to preserve the integrity of the compartment).

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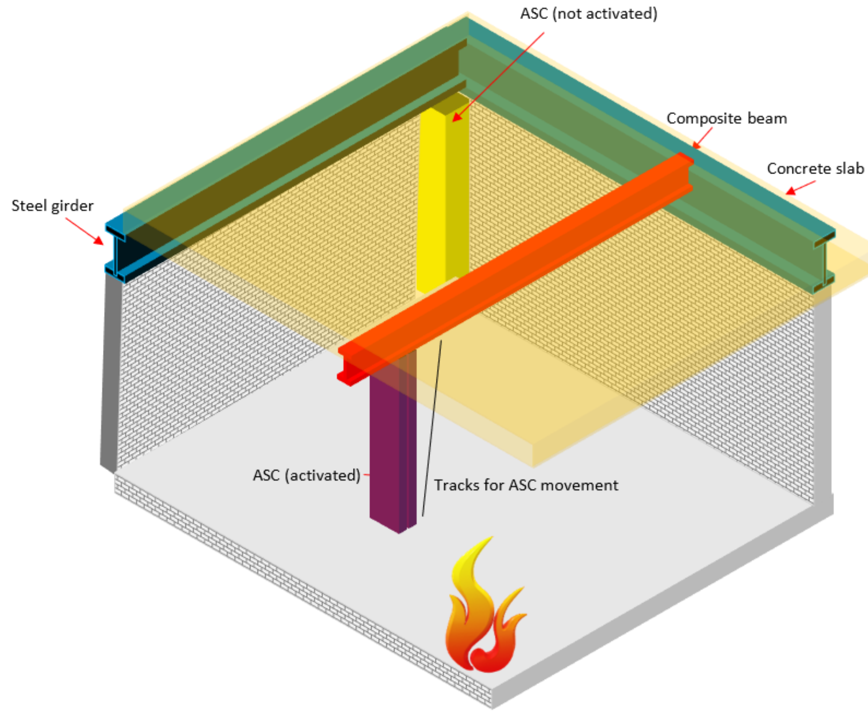
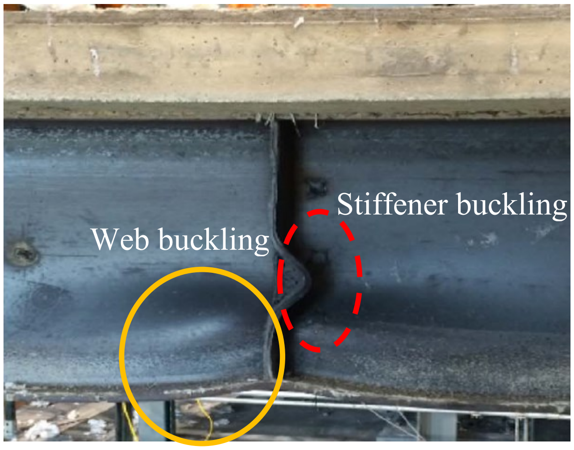


Fig. 2 Concept for an ASC

A note on the proposed framework

The application of CV towards understanding failure, or at minimum, damage of structural components/systems requires input and analysis of a large number of images or videos of damaged or failed structures (see samples shown in Fig. 3). It should be stressed that: 1) very limited instrumentations and laboratory equipment can withstand harsh loading conditions (e.g. fire), 2) the notion of a publicly available and properly compiled databases for such images/videos is technically foreign to this field (i.e. structural engineering), 3) the outcome of building/collapse investigations is often kept away from the public eye (i.e. for liability, insurance, legal etc. purposes), and 4) even when researchers carry out experiments, the accepted norm is to only share a sample of images of such tests in reports and research articles.



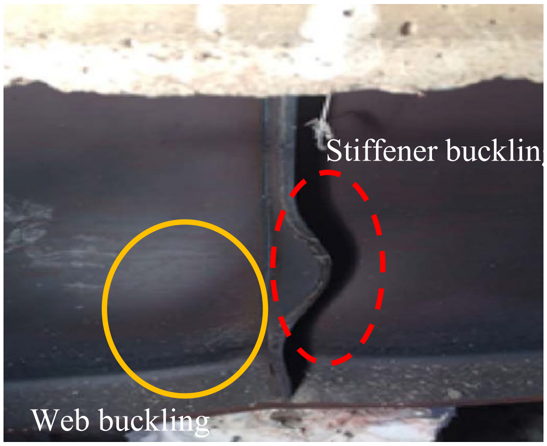


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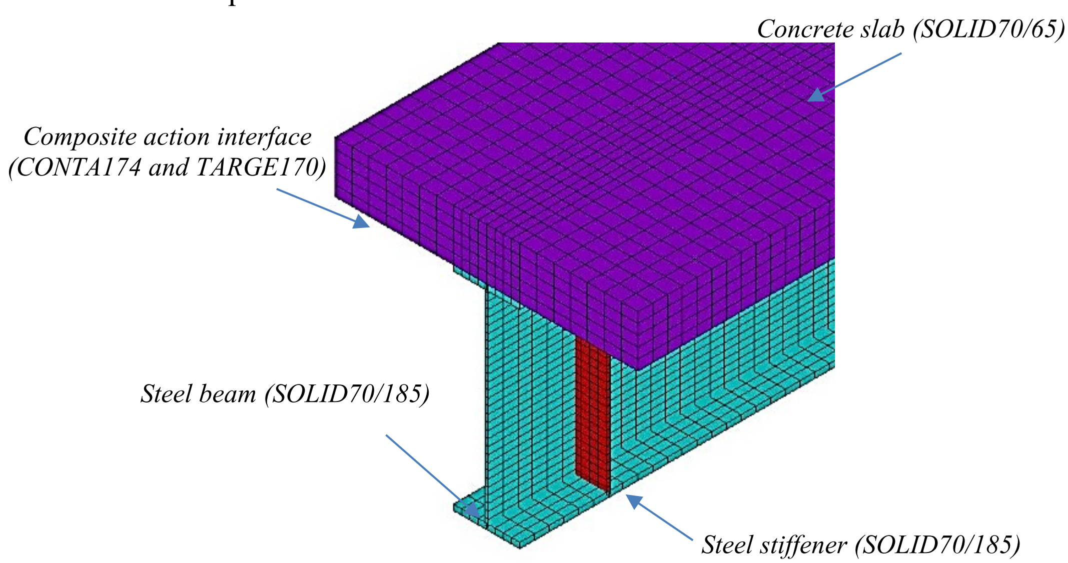
Fig. 3 Samples of failure due to temperature-induced instability (i.e. web buckling) in fire-exposed composite steel girders [32]

Thus, the availability of i) very few images, ii) taken from 1-2 vantage points, and iii) of low/medium quality, hinder their use and applicability into training and development of robust CV models. In order to overcome some of the above limitations, this study explores utilizing images of damaged structures taken from highly complex 3D nonlinear FE simulations that are based on actual full-size experimental tests. It should be noted that the above proposed framework is still expected to properly function when/if supplemented with actual imagery from failed structures. The following section better highlights the development of FE models that can be used for this purpose in more details.

DEVELOPMENT OF FINITE ELEMENT MODELS

The three-dimensional (3D) FE models used to generate imagery to be input into the CV platform were developed in the simulation environment; ANSYS. These models were built to mimic realistic behavior of structures and hence account for geometric imperfections and material nonlinearities. The same models also give due consideration to material-specific characteristics (i.e. damage softening and temperature-dependent properties) as well as failure limit states (i.e. flexure, shear, instability, deflection, debonding etc.). For undertaking FE analysis, two beams are examined. The first, Beam 1, is a two-span (continuous) composite steel beam exposed to fire and gravity loading and the second, Beam 2, is a cantilever reinforced concrete (RC) beam strengthened with carbon FRP (CRFP) sheets and subjected to cyclic loading simulating a seismic event (see Fig. 4) [33]. Due to the different loading conditions subjected to these two beams, each beam is discretized using a particular set of element types and is modeled through phenomena-oriented simulation techniques as discussed below.



(a) Cross-section view

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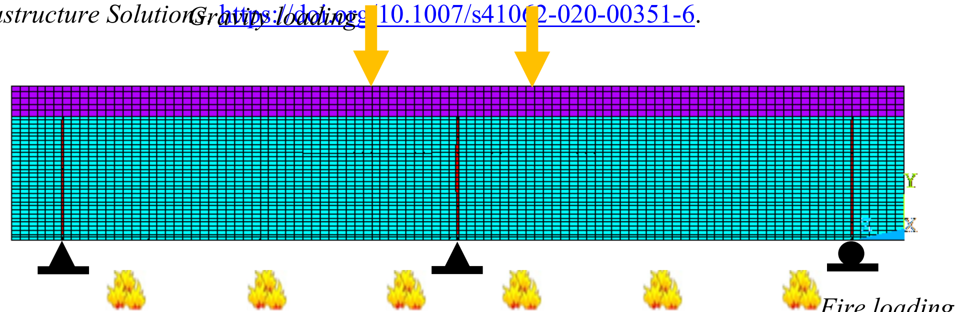
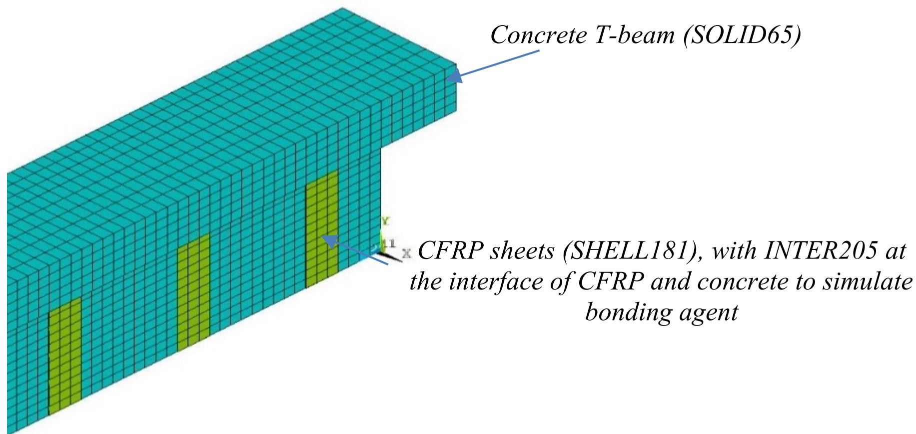
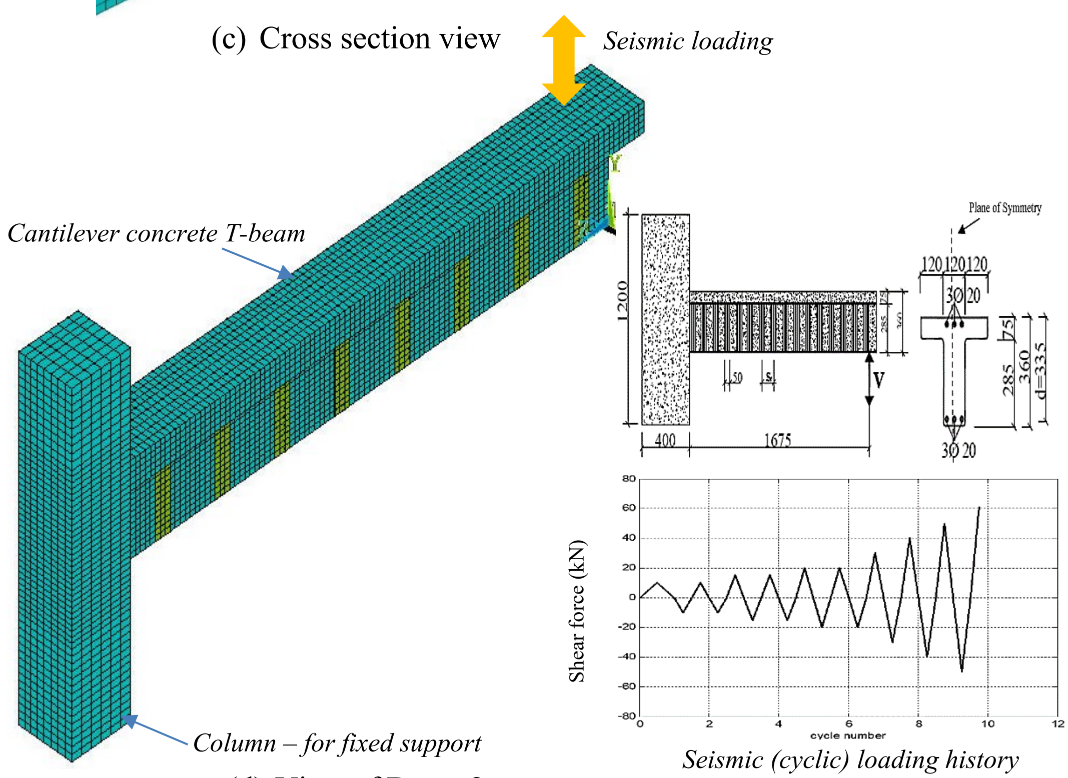


(b) Elevation view of Beam 1 (the distortion in steel beam is amplified to show geometric imperfections)



(c) Cross section view



(d) View of Beam 2

Fig. 4 Views of discretized composite steel beam and FRP-strengthened RC beam used in FE simulations

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Beam 1 – subjected to fire and gravity loadings

Beam 1 comprises of a hot-rolled W24×62 steel shape with flange width and thickness of 179 and 15 mm, as well as web depth and thickness of 610 and 11 mm, respectively (thus resulting in web slenderness of 55.1). This beam is fabricated using high strength low-alloy (HSLA) A572 steel of Grade 345 MPa. The steel beam is intended to be compositely attached to a reinforced concrete (RC) slab. To achieve 100% composite action, two rows of 19 mm diameter shear studs were welded to the top flange of the steel beam. The slab is cast with traditional normal weight concrete of a compressive strength reaching 45 MPa. This slab is reinforced with two layers of equally spaced steel reinforcement of No. 4 rebars. Both, the beam and slab, span 4185 mm.

Since Beam 1 is exposed to fire, this beam was discretized using distinct thermal and structural elements. For a start, the steel beam is meshed using two different types of thermal elements; SOLID70 and SURF152, as to simulate heat transfer generated from fire to the beam. For the structural analysis, the steel beam is discretized with SOLID185 while the concrete slab is meshed with SOLID65 to allow capturing cracking and crushing of concrete. The interface between the steel beam and RC slab is discretized using nonlinear contact elements (CONTA174 and TARGE170) to account for the bond-slip action that can develop under fire conditions. Proper restraint conditions are installed through restricting the movement and rotation of nodes at support conditions.

To accurately capture the fire response of this composite steel beam, temperature-dependent thermal and mechanical properties of structural steel, concrete, and shear studs are input into the developed FE model. These properties include density, thermal conductivity, specific heat, strength, modulus and stress-strain relations. These properties are assumed to be taken as recommended by the Eurocodes [34,35]. Other factors that govern heat transfer phenomenon such as convection and radiation are also accounted for as per Eurocodes provisions [34,35].

To properly simulate the thermo-structural response of this composite steel beam, two steps of simulations are required to be carried out. In the FE simulations, it is common to carry out a thermal-then-mechanical analysis. This practice has been well established by several researchers [36,37]. It helps to note that the amount of deflection and stresses arising from pre-loading the beam can be considered small (which justify the use of a thermal-then-mechanical simulation analysis). Thus, in the first step, heat transfer between fire source and composite beam is analyzed and the outcome of this analysis (i.e. propagation of temperature across the composite beam) is input to the second step of analysis. In the second step, gravity loading is applied (simultaneously to fire loading obtained from the first step) as to properly evaluate structural response of the beam. Failure of this beam is assumed to occur once sectional capacity (i.e. flexure/shear) falls below level of bending moment or shear force arising from applied loading or once beam's deflection exceeds the limit of ($L^2/400d$) or rate of deflection reaches ($L^2/9000d$); where L and d are the span and depth of the beam, respectively [38]. It is worth noting that failure in the full-scale fire test carried out on this beam occurred through development of high levels of temperature-induced web instability (i.e. buckling) at the interior support within the heating phase [39].

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Beam 2 – subjected to seismic loading

Beam 2 is also modeled using ANSYS. This beam is supported from one end by a RC column, while being cyclically loaded at the free end (see Fig. 4d). This cantilever beam has a clear span of 1675 mm, with a depth of 360 mm, web width of 120 mm, flange thickness of 75 mm and flange width of 360 mm. The beam is reinforced with top and bottom steel reinforcement, comprising of three 20 mm diameter rebars. This beam is strengthened with 50 mm wide Sikawrap 160c CFRP sheets adhesively bonded with Sikadur-330 epoxy as this beam is designed to be deficient in shear (i.e. was not reinforced with stirrups) [33].

The different components of this RC beam are discretized such that SOLID65, LINK8, SHELL181, and INTER205 elements are used to mesh concrete, steel rebars, and CFRP sheets, respectively. As this beam is only subjected to cyclic loading at ambient conditions, only mechanical (i.e. strength, modulus and stress-strain relations) properties are required to be input. Thus, the compressive behavior of concrete is modeled through Hongnestad et al. [40] model, while its tensile behavior was modeled through a trilinear model based on the work William and Warnke [41]. The CFRP sheets are assumed to have orthotropic properties with elastic properties while epoxy has brittle and isotropic elastic properties. The epoxy is applied between the CFRP sheet and concrete faces and is simulated through a cohesive zone model developed by Xu and Needleman [42]. The beam was fully retrained on one edge to represent a cantilever beam by fully constraining the nodes' movement and rotations. Similar to Beam 1, the second beam is also assumed to fail once its sectional capacity is exceeded and can also fail once debonding or fracture of the CFRP sheets occur.

Validation of FE Models

In order to validate the aforementioned FE models, numerical predictions were compared against observations from full-scale tests carried out on Beam 1 and 2. Figure 5 shows a comparison between experimentally measured and numerically predicted results for Beams 1 and 2; wherein thermal (i.e. temperature rise across the beam) and deflection results are plotted for Beam 1, and hysteresis history is plotted for Beam 2. Overall, it can be inferred from this figure that there is a close agreement between experimentally measured and predicted outcome of the FE simulations. A general rule of thumb for a well-developed FE model is to have a Newton-Raphson based convergence limit of 5% as to achieve an accuracy of 5-10% of that observed in the actual tests. It should be noted that a detailed discussion on the carried out experimental tests, together with the development and validity of the FE models, is presented elsewhere [33,39] for brevity as the main focus of this study is to use FE models to generate images that can develop a CV tool capable of evaluating structural response under extreme loading conditions.

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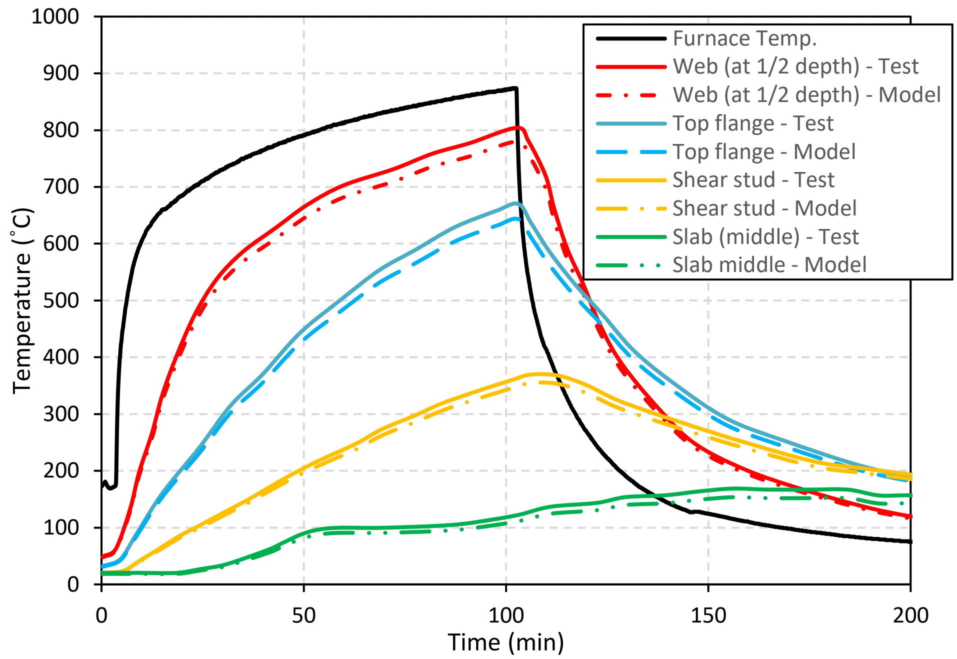
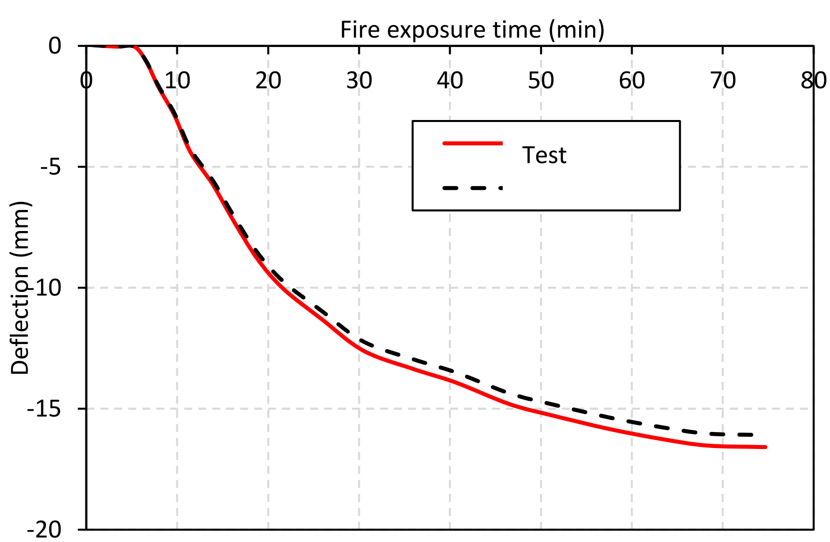


(a) Thermal response in Beam (Note: the cooling phase is shown for completion and refers to the end of fire test (and hence cooling of furnace). This phase does not affect the findings of this work since failure occurs during the heating phase (as observed in the real fire test).)



(b) Deflection response in Beam 1

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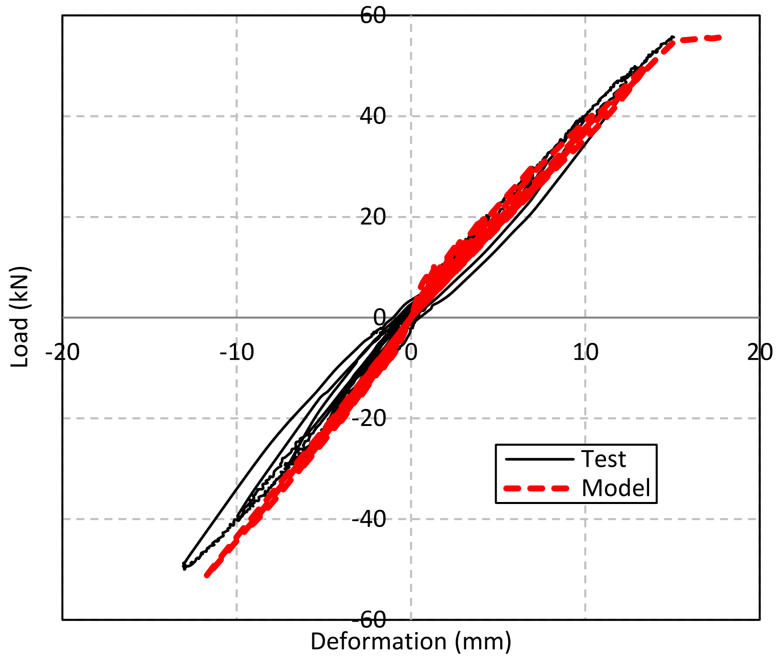

(c) Hysteresis history in Beam 2
Fig. 5 Validation of the developed FE models

STRUCTURAL ASSESSMENT THROUGH CV

In order to carry out a CV analysis on the above described beams, a CV model was developed through the commercially available AI-based image recognition platform; Deepomatic. Deepomatic can be used to build custom-designed CV models to extract meaningful information (referred to as concepts) from abstracts, images and videos. In a CV-based classification analysis, a CV model aims to classify a particular object through extracting visual cues and then determining which category best fit this object. A successful CV model will be able to detect pre-identified features in a given visual (e.g. buckling of web in steel beams or flexural and shear cracks in a concrete beam).

A sample of such categorization images pertaining to Beam 1 and Beam 2 are shown in Fig. 6. This figure traces the development of failure mechanisms in these beams during fire and earthquake loading scenarios. The same figure also shows schematics and definitions of concepts used to identify failure mode/mechanisms in Beam 1 and Beam 2. For example, the concepts used in the case of Beam 1 are associated with development of web buckling failure mechanism at the interior support of this beam. As such, Fig. 6a shows how this failure mechanism develops over fire exposure time (i.e. no sign of buckling at the beginning of fire, then minor buckling starts to occur at round 25 minutes of fire exposure due to heat and loading effects, and a much larger area of the web undergoes substantial buckling at around 60 minutes etc.). Similarly, Fig. 6b distinguishes between intensity and different types of cracks in Beam 2 (i.e. tensile vs. compressive vs. shear cracks). Based on the results of the CV analysis, an assessment can be made to recommend possible solutions and repair strategies as to retrofit or salvage damaged structural members.

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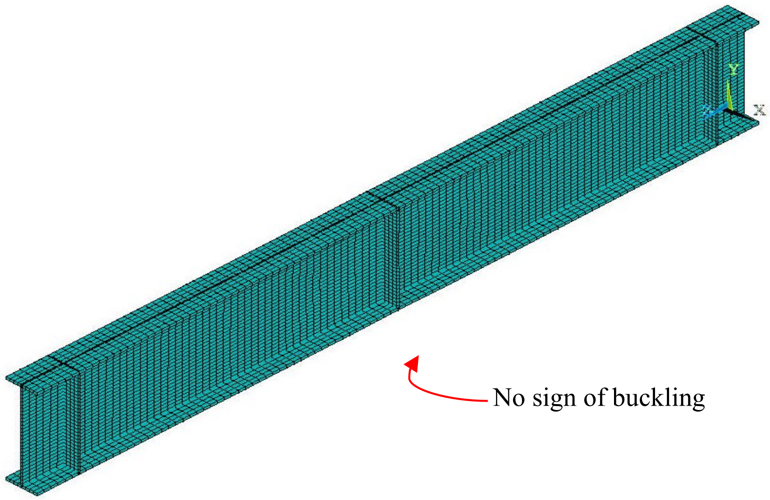
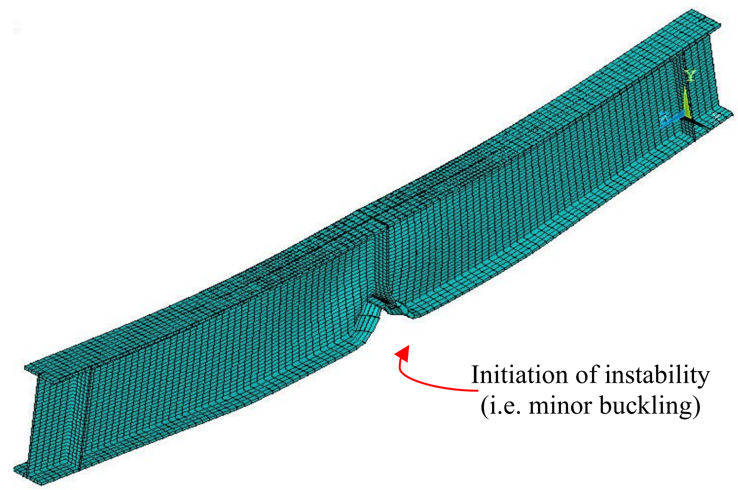
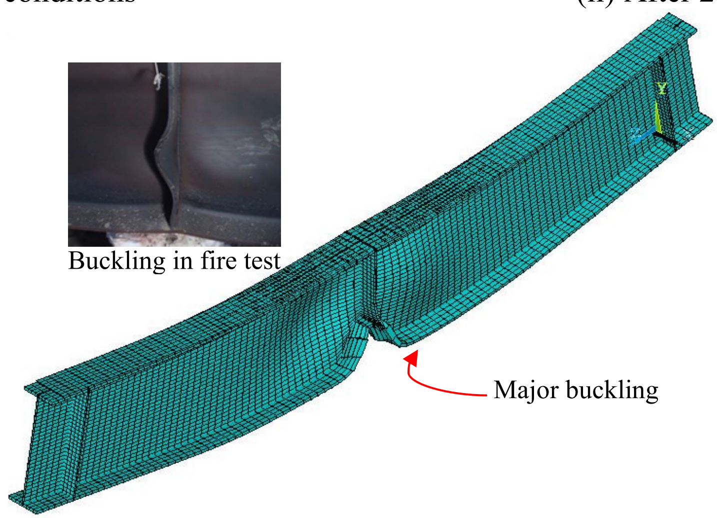


(i) Ambient conditions



(ii) After 25 minutes of fire exposure



(iii) After 60 minutes of fire exposure (and comparison against previous full-scale fire test)

(a) Propagation of failure in fire-exposed steel composite beam (Beam 1) through temperature-induced web buckling

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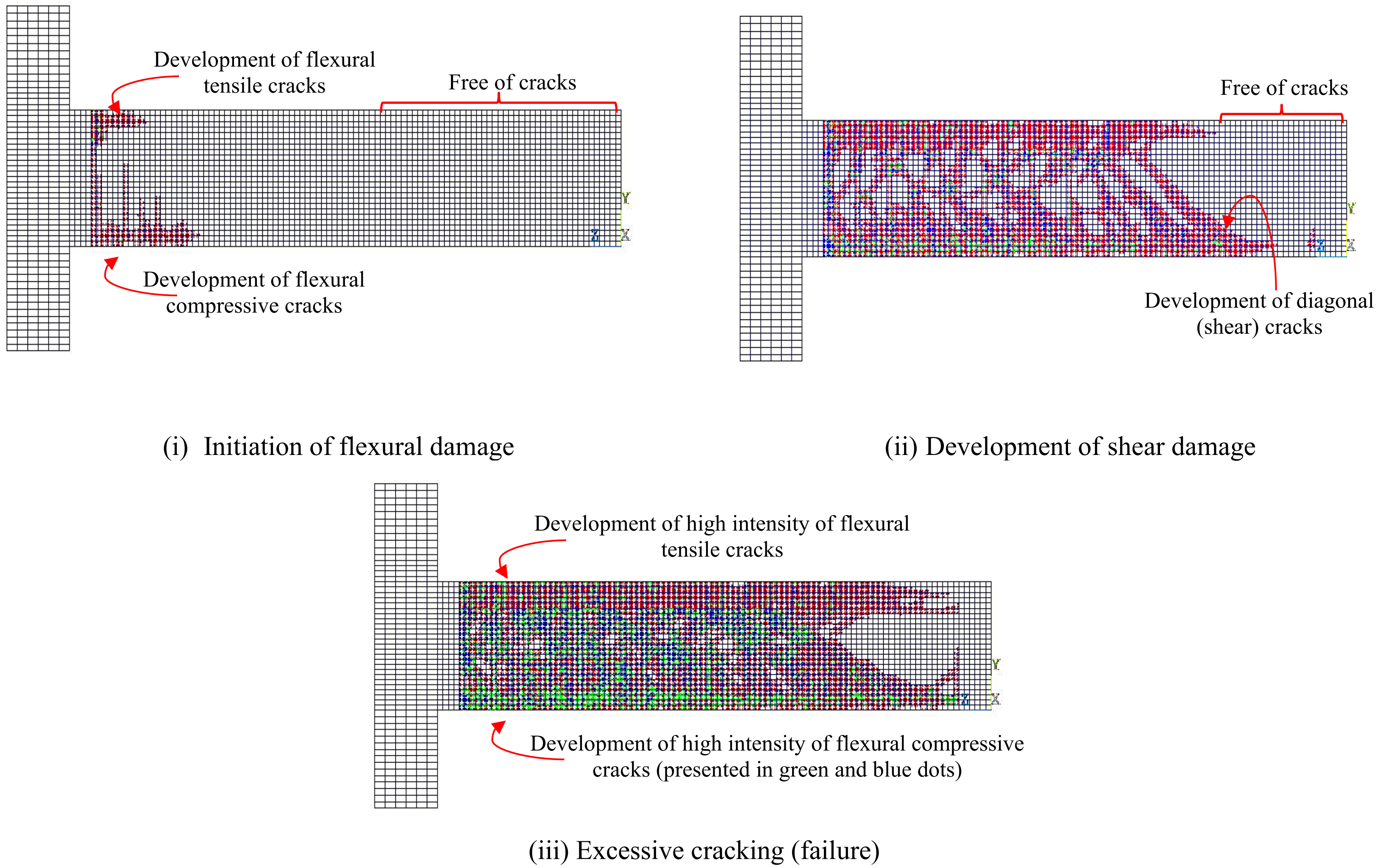

(b) Crack development history in Beam 2 under seismic loading

Fig. 6 Definition of concepts and history of failure/damage mechanisms in Beams 1 and 2

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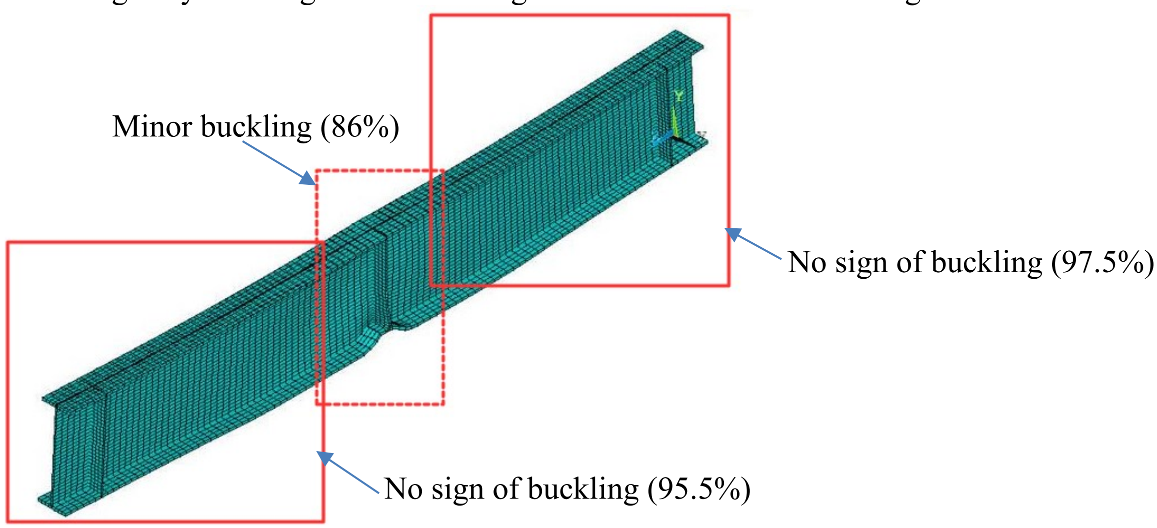
Outcome of CV analysis on Beam 1

In the case of Beam 1, images tracing development of temperature-induced instability from the start of fire until failure, in 30 seconds increments, are input into Deepomatic; and the complete list of these images is shown in Appendix 1. Out of 141 images, 107 images were used to train the CV model while 31 images were used to validate this model. This split of 77.5%/22.5% was selected to be in close proximity of recommendation of notable works. The training process included identifying three concepts: 1) no sign of buckling, 2) minor buckling, and 3) major buckling. In this process, the CV model is trained by inputting images that were labelled with one (or more) of the three aforementioned concepts. Then, the CV model is trained by selecting one of the architectures adopted by Deepomatic. In the case of Beam 1, the architecture with the best performance was Faster RCNN - ResNet-101 v1. A sample of the outcome of this analysis that is taken on images labeled for testing (i.e. not used in training or validation of the model) is shown in Fig. 7 which depict the state of the beam after 13 and 65 minutes of fire exposure. In Fig. 7a, the CV model was able of accurately identifying the magnitude of temperature-induced damage occurring at 13 minutes of fire exposure as minor buckling with 86% confidence and also detected that end panels did not undergo any buckling with a much higher confidence level exceeding 95%.



(a) At 13 minutes

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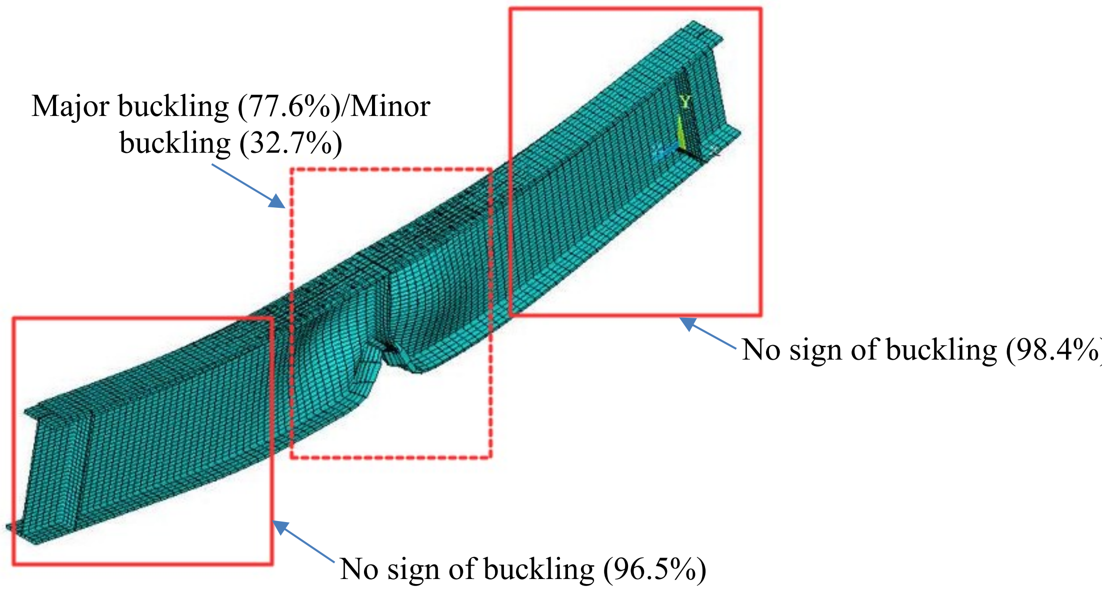

(b) At 65 minutes

Fig. 7 Predictions from CV model in case of Beam 1

Figure 7b shows that the CV model managed to also detect that exterior panels of this beam did not undergo any buckling after 65 minutes of exposure to fire and this agrees well with observations from a full-scale fire test carried out earlier [32]. In addition, the CV model identified the magnitude of buckling at the mid-span region as major buckling with high confidence 77.6% as oppose to being minor buckling (32.7%) at the same region and point in time. It should be noted that major buckling was observed to occur at a similar point in time as documented in the fire test [32].

Outcome of CV analysis on Beam 2

An autonomous and cognitive infrastructure has the ability to carry out full diagnosis post an extreme event as to estimate magnitude of damage, as well as propose suitable strategies for retrofitting, safe inspection and timely repairs. As discussed earlier, Beam 2[*] is subjected to a series of cyclic loadings representing a seismic event. Similar to the procedure carried out in evaluating Beam 1, images obtained from the FE simulations relating to development of flexural and shear cracks in this beam during the loading history are input into the CV model. For simplicity and to show the potential of the developed CV model, only few images are used to train, validate and test the model. This decision was made to represent a practical case study in which a limited number of images are available for analysis. It should be noted that a sample set of images used herein (comprising of 8 images for training and 2 images for validation) are plotted in Fig. 8.

[*] For the sake of discussion carried out herein, Beam 2 is examined first without accounting for the contribution of CFRP attachments (i.e. transforming this beam into a traditional RC beam). Beam 2 is then re-examined (with CFRP attachments) towards the end of this section.

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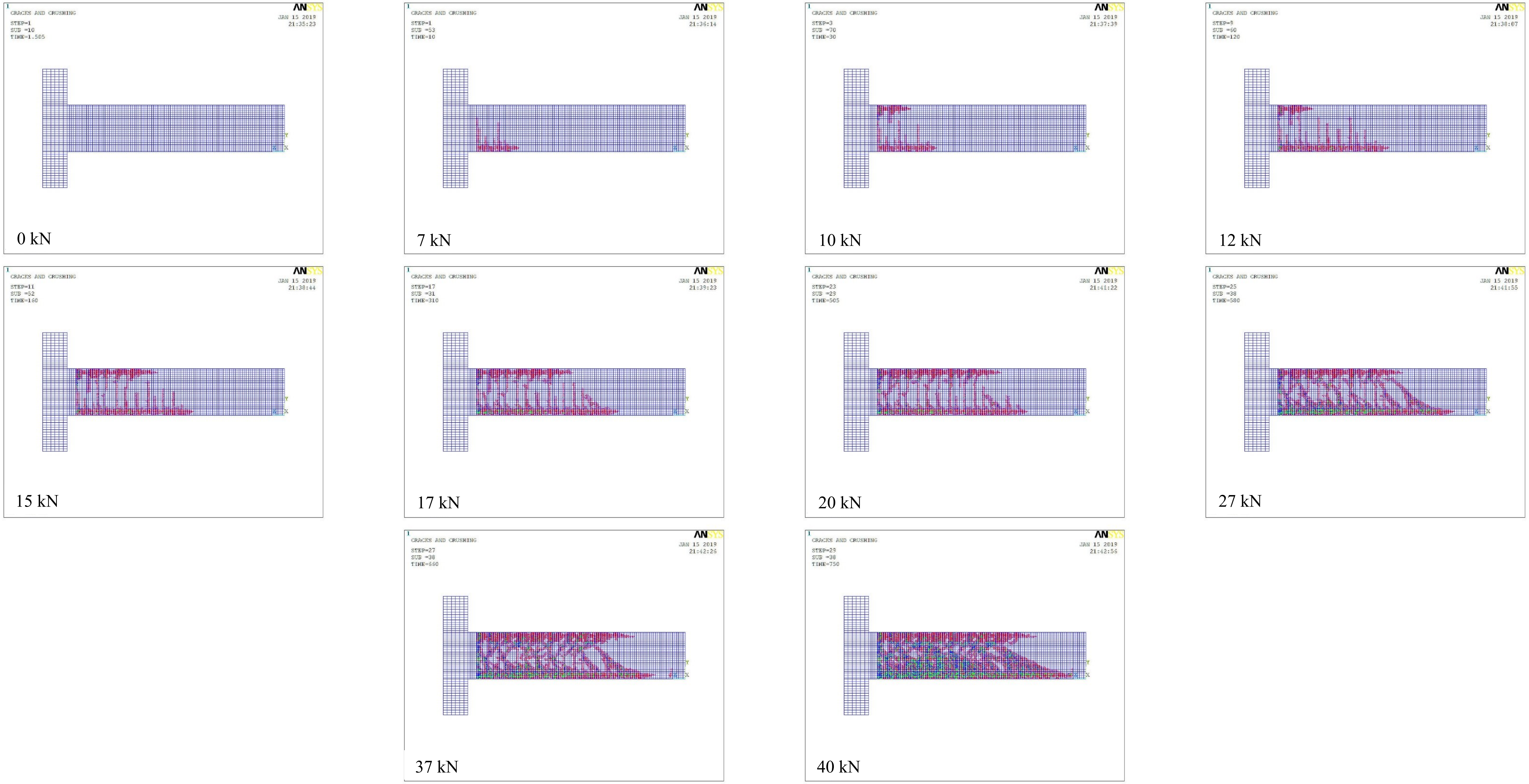

Fig. 8 Imagery used in training the developed CV model in case of Beam 2

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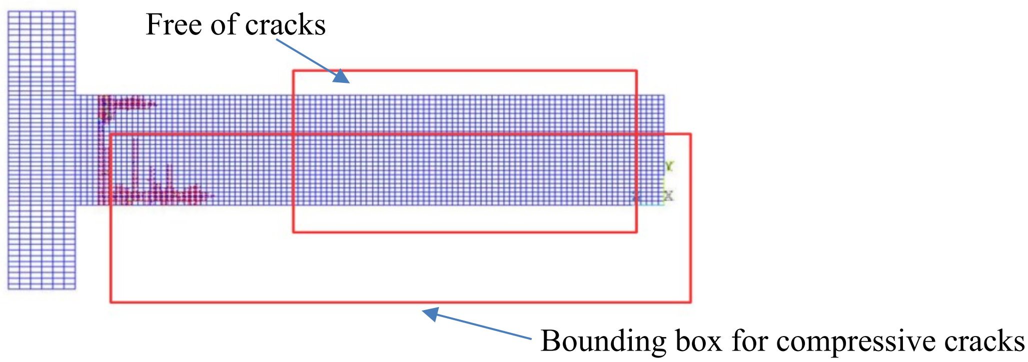
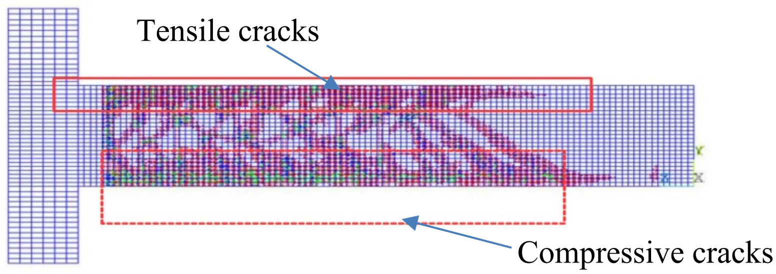
Once the CV model was properly trained to identify compressive, tensile, and shear cracks as well as regions free of cracks; using Faster RCNN - ResNet-50 v1 architecture, the developed CV model was able to identify the type of developed cracks in the images used for validation and shown in Fig. 9. A cross examination of this figure shows that predictions from the CV model seems to better capture the development of cracks under high magnitude of loading (at 30 kN) more than that under lower magnitude of loading (at 10 kN). Moreover, predictions from the CV model seem to overestimate the size of compressive cracks (e.g. falsely classifying the region free-of-cracks located at the bottom portion of the beam) when the beam was subjected to a loading equivalent to 10 kN. Both of these observations can be simply attributed to the limited number of images used in training the developed CV model (8 vs. 107 images as used in Beam 1). In the case where a higher number of images is to be used, similar to that shown in Beam 1, then the CV model is expected to achieve higher recognition performance in the case of Beam 2.



(a) At 10 kN



(b) At 30 kN

Fig. 9 Predictions from CV model in case of Beam 2

The result of the above examination can still be used to: 1) quantify the magnitude of damage, and 2) propose suitable strategies for retrofitting. Through close examination of Fig. 9b, an effective strategy that can be used to repair the heavily cracked or damaged beam is through utilizing carbon fiber-reinforced polymers (CFRP) [43–46]. Thus, this beam was strengthened with 0.12 mm thick and 50 mm wide CFRP sheets that are spaced at 135 mm center-to-center across the longitudinal side of the beam. In order to examine the viability of this solution, the structural performance of this strengthened beam is evaluated under the same loading history applied to the beam without any FRP attachments using the FE model developed earlier (see Fig. 4d). The outcome of this numerical analysis is plotted in Fig. 10 to compare the structural performance in terms of cracking vulnerability of the unstrengthened RC beam to that of the FRP-strengthened beam. Figure 10 clearly shows how adopting FRP strengthening as a repair strategy seems to be an effective solution as apparent by the lesser magnitude and intensity of cracks developed at 7 and 40 kN.

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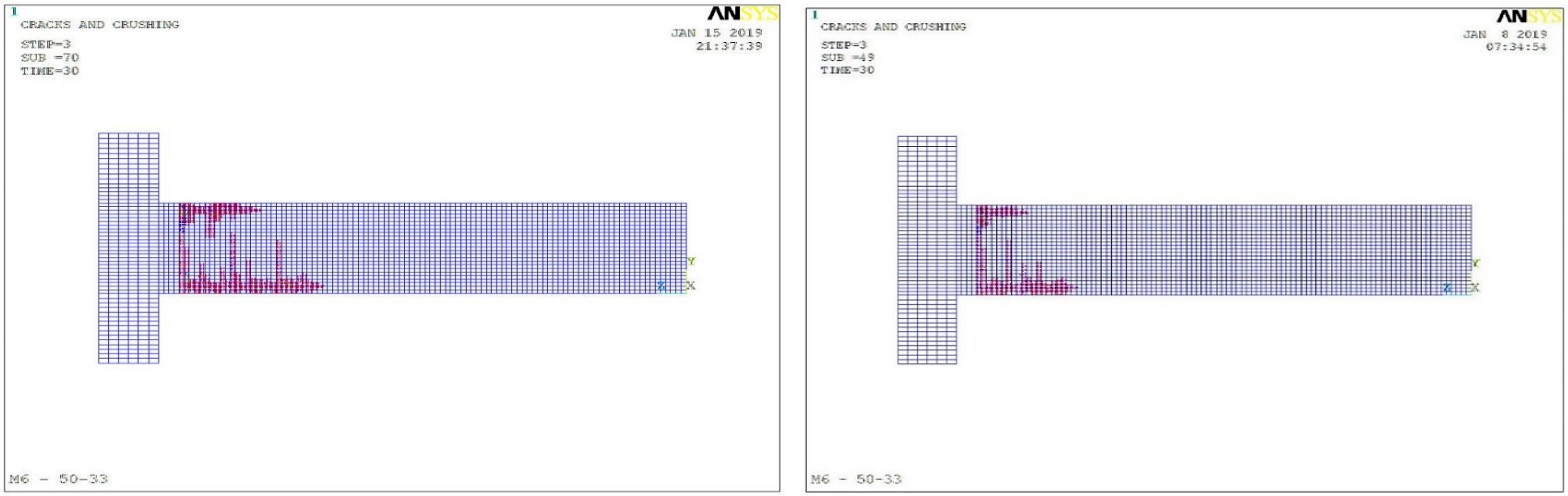
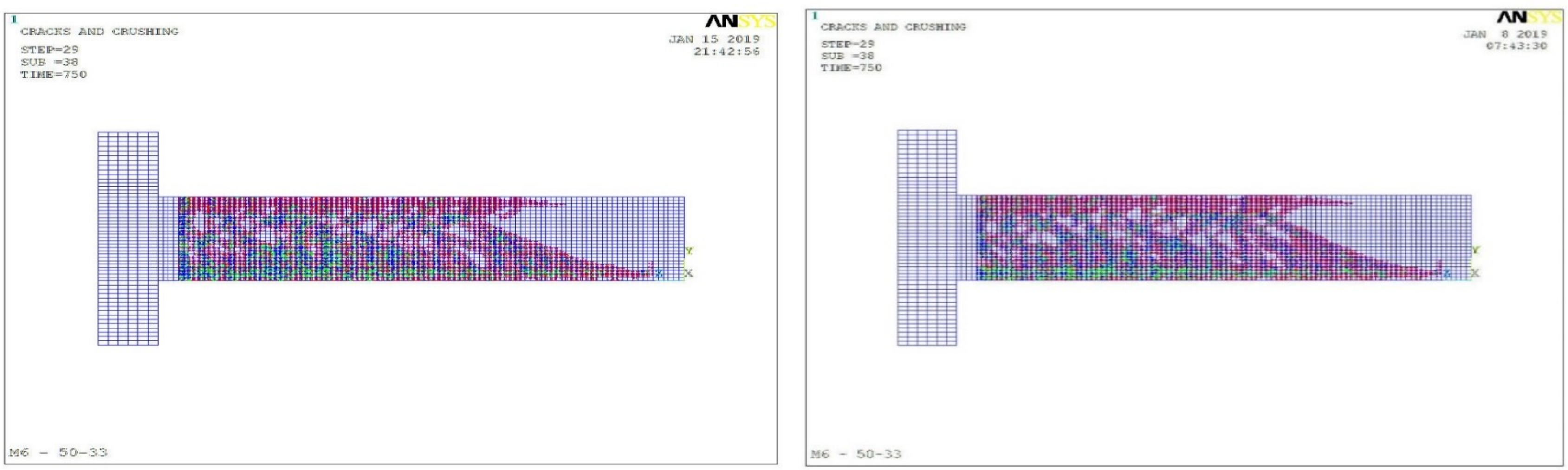


(a) At 7 kN



(b) At 40 kN

Fig. 10 Comparison between crack development in RC beam (left) and FRP-strengthened RC beam (right)

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It should be noted that a future study, that is currently underway, is designed to utilize CV to better visualize the magnitude and intensity of cracks in beams similar to Beam 2. This study is exploring a few repair solutions including: FRP strengthening composites, fiber reinforced cementitious matrix (FRCM), mortar injections, metal jacketing etc. For example, once the CV model identifies minor cracking such as that shown in Fig. 10a, then this model would recommend the use of mortar injections over installing metal jacketing or FRP attachments across the whole beam; given strength and serviceability reequipments, as well as expected economic costs etc.

INSIGHTS INTO CURRENT CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The discussion presented throughout this work infers that in order to integrate CV to enable structural awareness and self-diagnosis as a step towards realizing autonomous structures, then a coherent framework is needed. This framework is to be easy-to-deploy, and most of all scalable, and reliable. As such, there is a need to first identify the required combination of soft/hardware, type and nature of AI/CV algorithms/models, sensors, communication and processing architectures etc. A key component to remember is that the amount of data that is expected to be generated before/during/post a disaster breakout, given the scale of an infrastructure, can be quite substantial (unlike those presented herein). Hence, appropriate means are required for proper data segmentation, pre-processing and post-processing of imagery as to arrive at meaningful representation of collected data that can be further processed with ease and in real-time basis [47].

Other factors that warrants further research and need to be addressed include: type, sensitivity, power supply, power consumption, life-span of sensors (i.e. image collectors such as cameras etc.), sensor network, required bandwidth, data sorting and collection etc. Future advancements in analytics and computer vision will be able to handle the above challenges with ease (with the rise of faster processors and image capturing technologies). Until then, this should not deter us from pursuing this research and planting seeds for an approach that can tackle such a problem. A key item to consider is the cost associated with installing sensors and processing of data etc. In a way, there is a need to standardize a proper installation procedure that ensures maximizes "meaningful" data collection. Without attaining an affordable collective system, the merit of the proposed analysis remains limited. Realizing cost effective solutions to the above identified challenges are essential to the success of cognitive and autonomous structures.

While this work utilized images obtained from FE simulations, primarily due to challenges in obtaining imagery from full-sized experiments, the presented framework can also be applied using representative images taken from actual tests. Such images would perhaps not be of "crystal clear" quality and are most likely to have distinct features than those obtained from FE numerical simulations especially with regards to depth, uniformity, neatness, roughness, color index etc. As a result of these unique features, CV architectures are likely to be adjusted to properly address such features, as well as to improve their computational competence. As discussed earlier, the appendix contains a collection of images obtained from the developed FE simulations on Beam 1. This collection only contains 141 images. It should be noted that all of these images are taken from one angle of view and for an induvial (i.e. isolated) structural member. While this might limit the practicality of a developed CV model, this still provides a good starting point for training CV

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models[†]. Future works are asked to focus on much more complex structural systems/members such as frames, joints, connections etc. In addition, researchers are invited to develop means to carry our tests, increase the size of imagery by augmentation or additional simulations.

It should be noted that while this work emphasizes the structural awareness of critical infrastructure, still an autonomous structure is expected to get feedback from other (non-structural) components such as: human factors i.e. occupants/commuters/first responders, as well as incident duration and magnitude etc. As such, an autonomous structure may alter its internal layout once the outcome of the complex processing of inputs collected from structural, human and incident components converge. Thus, upcoming studies are invited to cover various features of human behavior and disaster development and how these aspects can influence the autonomy and cognitivenss of an infrastructure [48]. Future structural systems, when supplemented with such abilities, are expected to have improved redundancy and resilience.

It goes without saying that the successful deployment of the proposed framework into practical scenarios requires the ability of such a framework to survive harsh loading conditions other than those discussed herein (i.e. tornados, tsunamis etc.) as well as to maintain reliability and accuracy during and post an extreme (or a series of events) [49]. A system of this magnitude, especially if to be scaled over a critical infrastructure i.e. super-tall high-rise building etc., is expected to be inherently intricate and to be designed with high redundancy. In this view, it can be seen that such a framework can only be realized through a fruitful collaboration between interdisciplinary researchers. For example, while computer scientists may take the lead on developing novel AI/CV algorithms with high prediction and processing capabilities, structural engineers on the other hand are expected to refine (or help improve) the state of these models to best fit the needs of civil construction. On a similar notion, both mechanical/robotics and structural engineers can collaborate on designing ASCs and so forth [50]. It is worth noting that issues with regard to standardization, privacy, security, and policy making (among others) are also expected to arise with future advancement, whether as a main concern or as a residue of other matters. Research and latest developments on such factors, while are not covered herein, can still be found elsewhere [51–53].

CONCLUSIONS

The outcome of this work allows examining the performance of structures, whether during or in the aftermath of a traumatic event, in real-time. The outcome of this work infers that CV can supplement current efforts aimed at realizing autonomous and cognitive (self-diagnosing) structures and facilitate safe inspections and immediate repairs. The following conclusions could also be drawn from the results of this investigation:

- Modern technologies such as CV are crucial to realizing autonomous and cognitive infrastructure.

[†] For instance, Deepomatic suggests the use of large volumes of imagery (i.e. exceeding 1000+ images) in order to achieve high confidence CV models.

- Current CV platforms are capable of detecting damage arising from extreme loading events such as fire and earthquake with high confidence exceeding 77%. Future CV models are expected to detect other loading events such as tornados, blast, impact etc.
- Future works are encouraged to develop platforms that link CV, occupant behavior structural engineering, inspection principles as well as repair strategies into one framework to enable synergy and effective utilization of the proposed concepts. These works are to explore various aspects such as software implementation, structural tolerance, connectivity, scalability etc.

Acknowledgment
The author would like to thank the support and constructive comments of the Editor and Reviewers.

Compliance with Ethical Standards
The author does not have any conflict of interest.

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This is a preprint draft. The published article can be found at: https://doi.org/10.1007/s41062-020-00351-6

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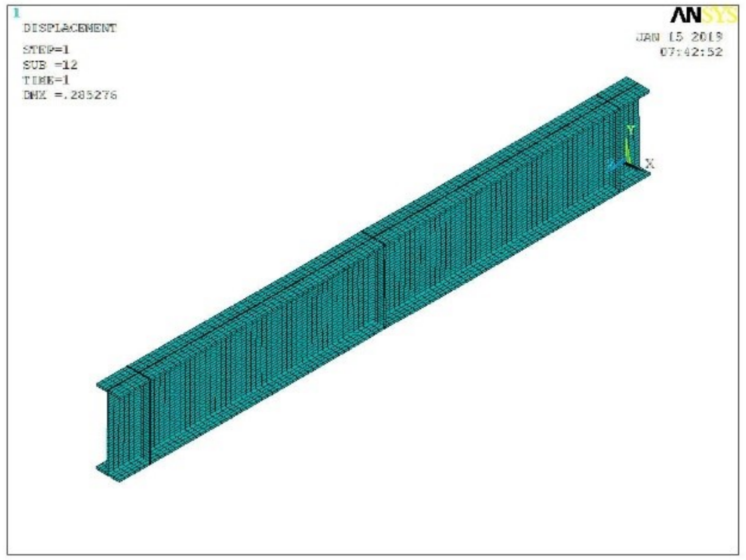
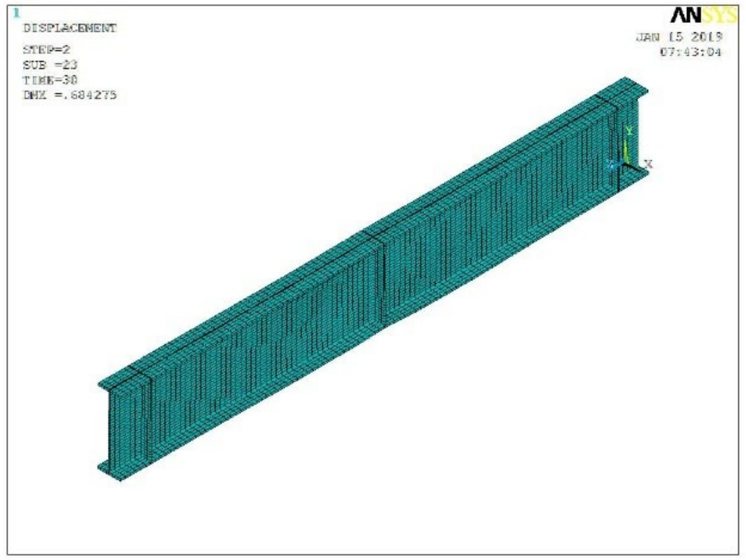
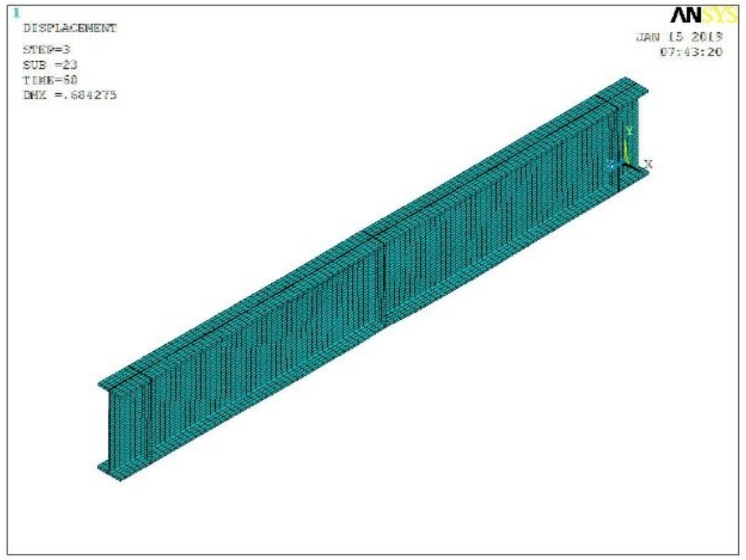
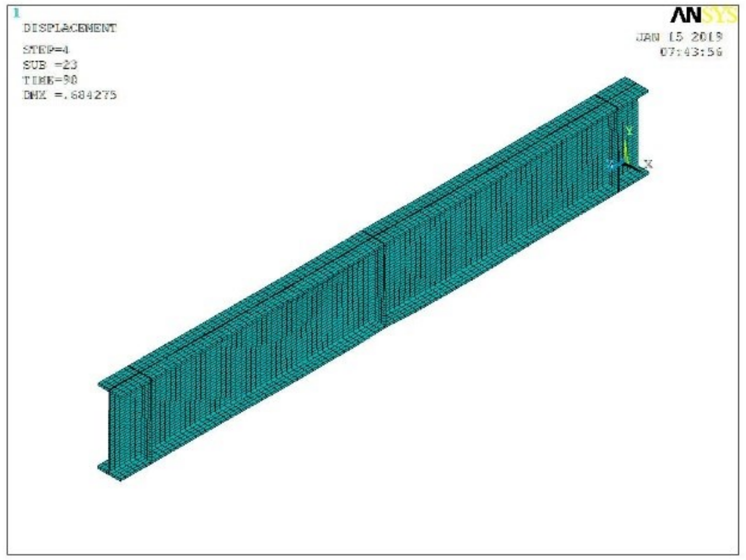
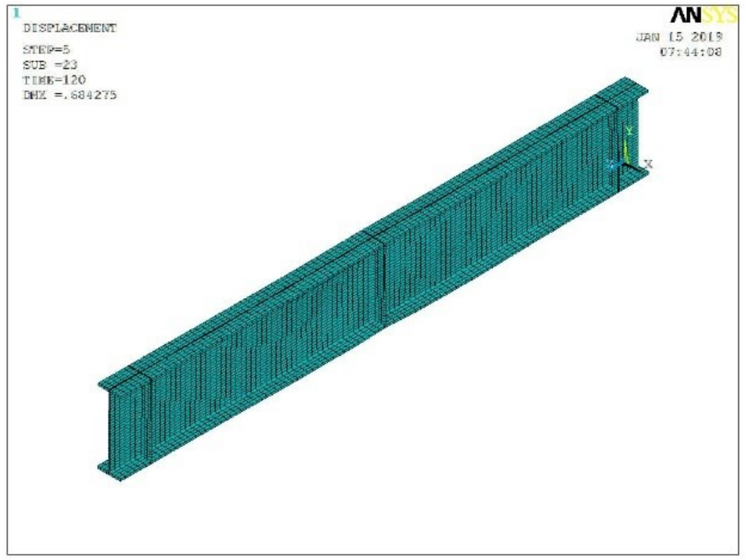
Appendix: The following images can be used to benchmark structural and construction engineering-based CV software (for a composite steel beam loaded in shear and subjected to standard fire conditions).

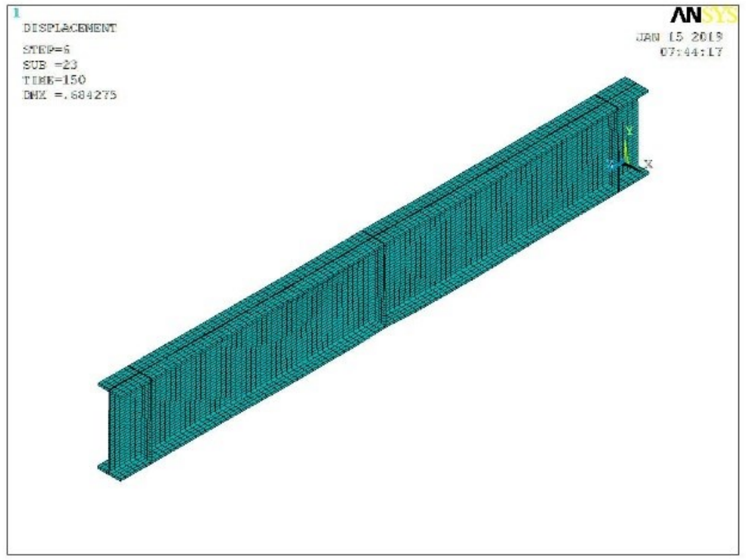


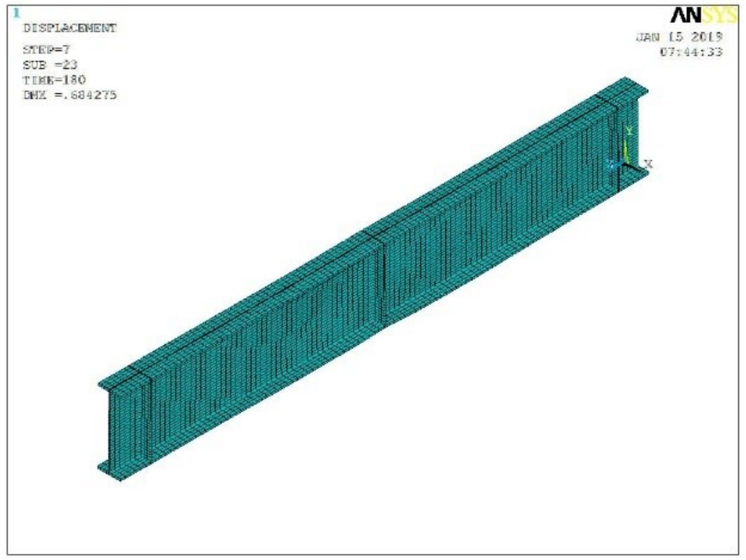


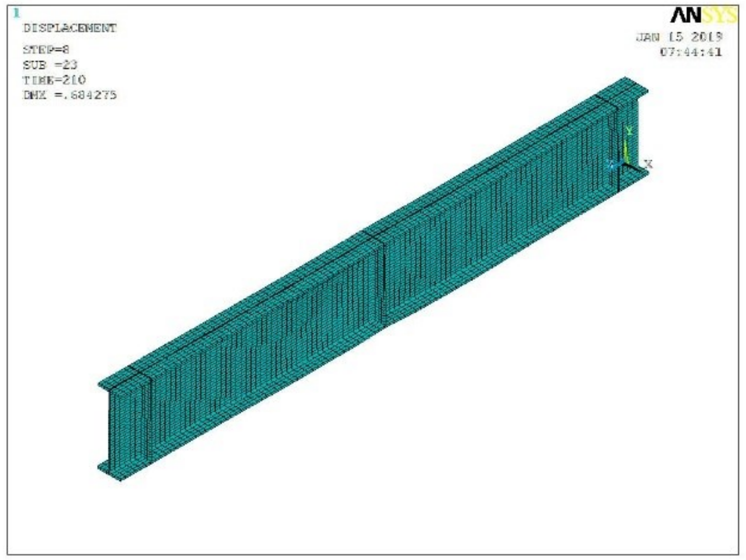


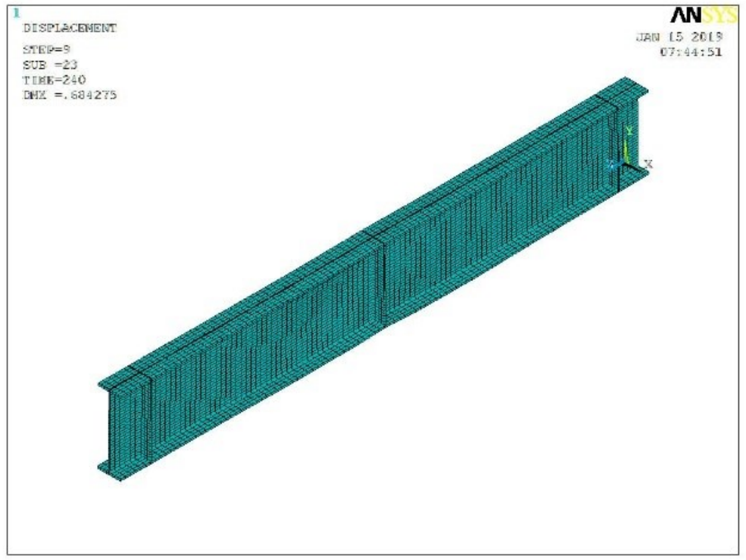












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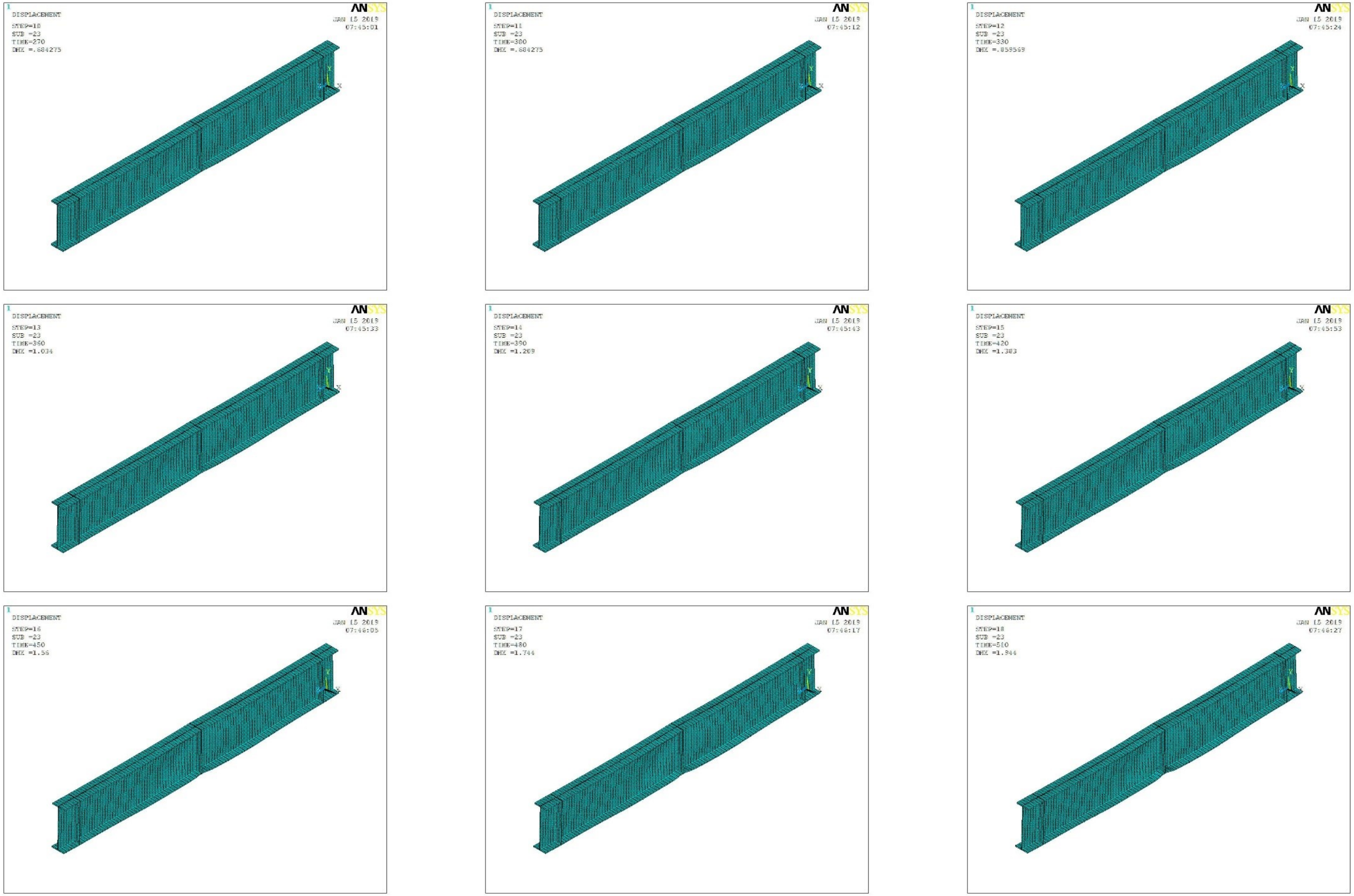

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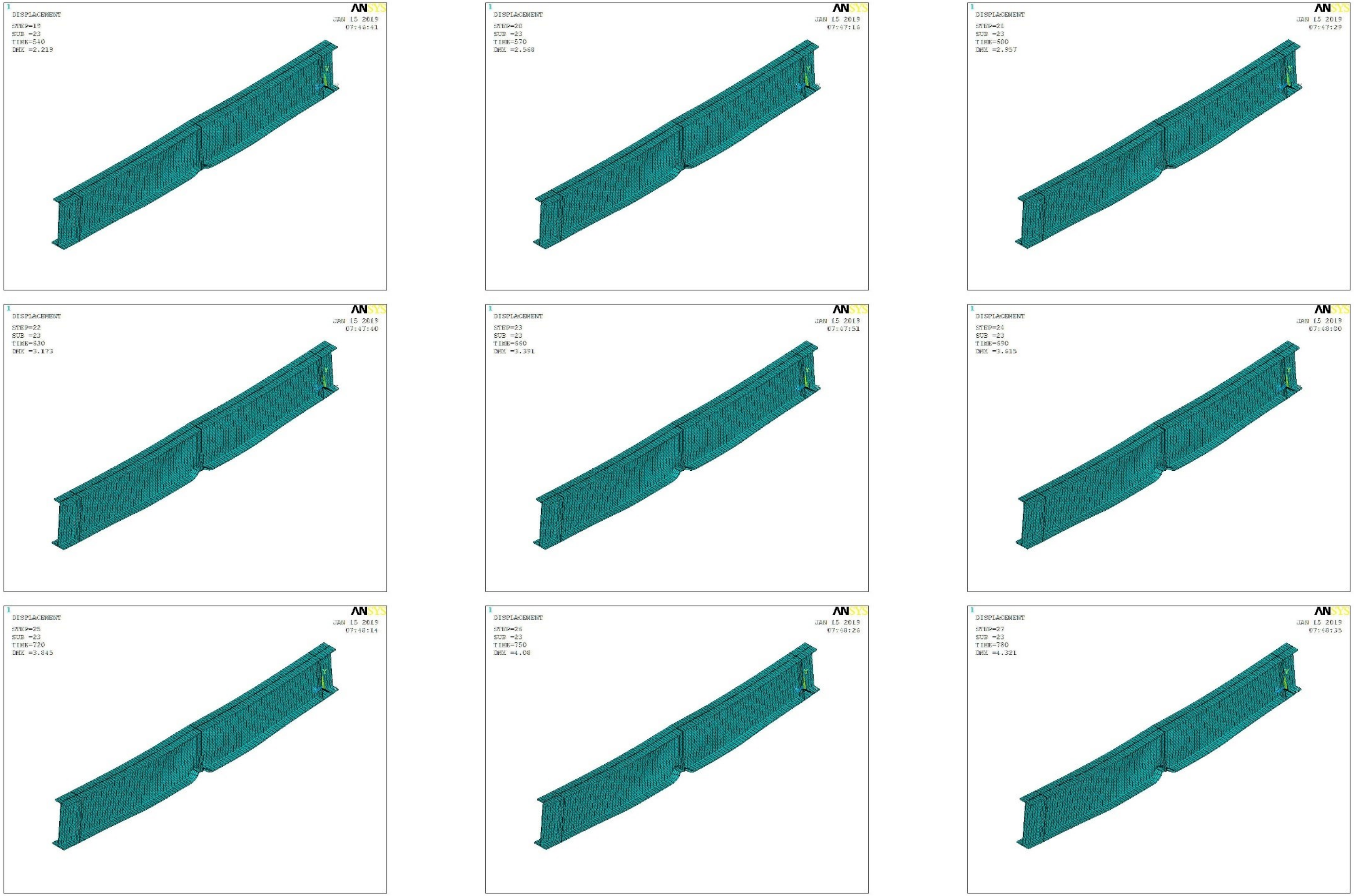

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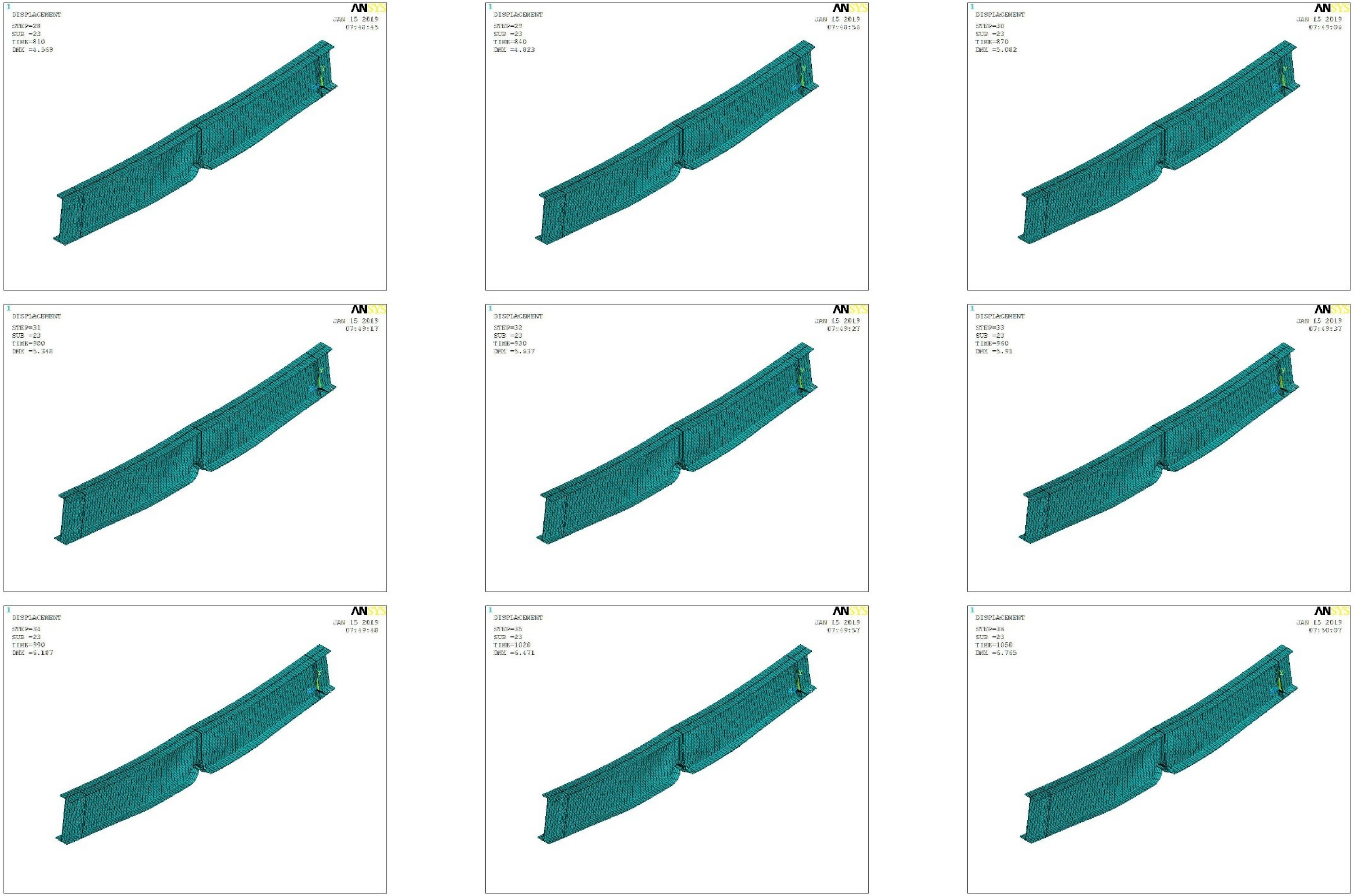

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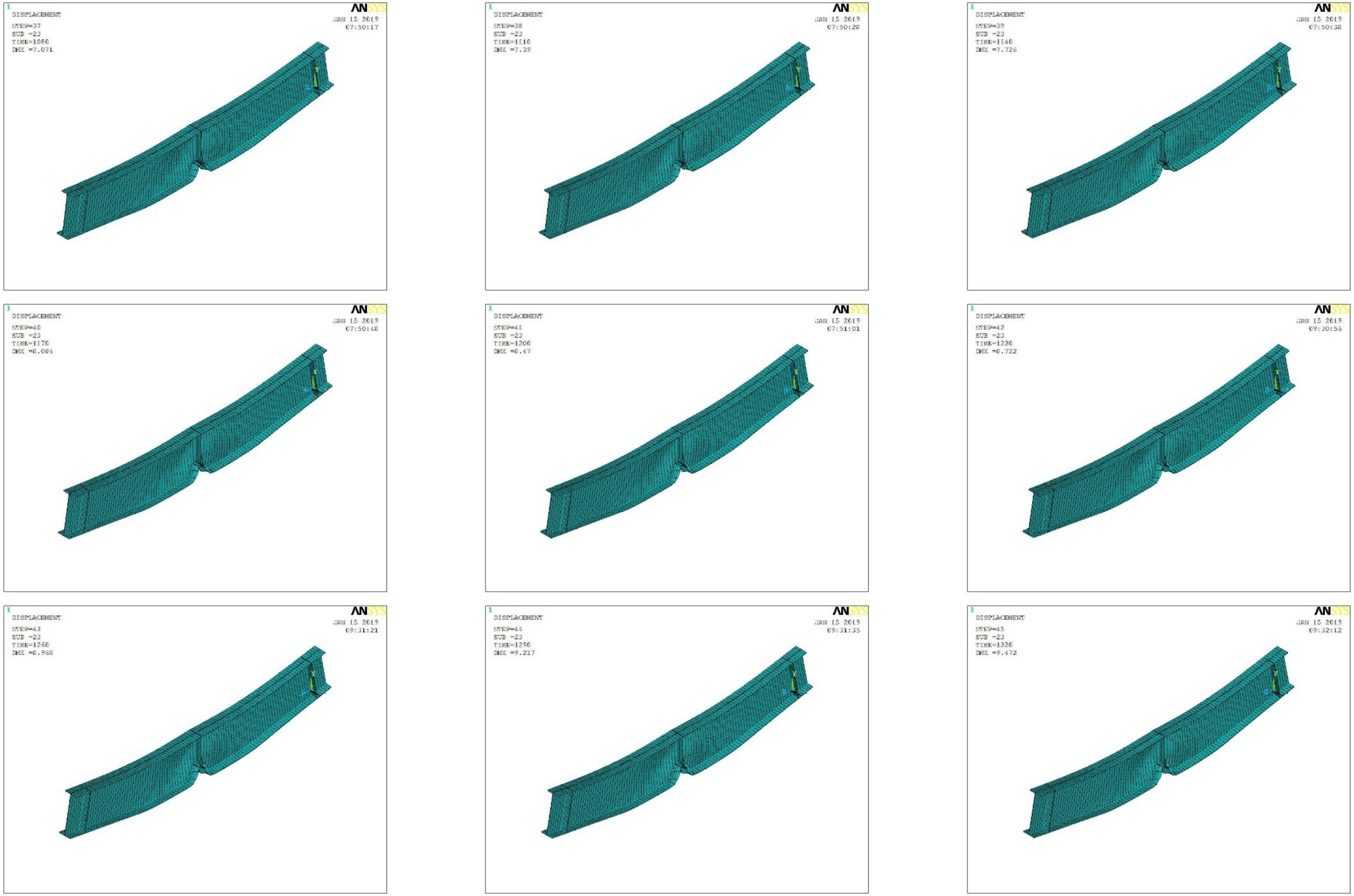

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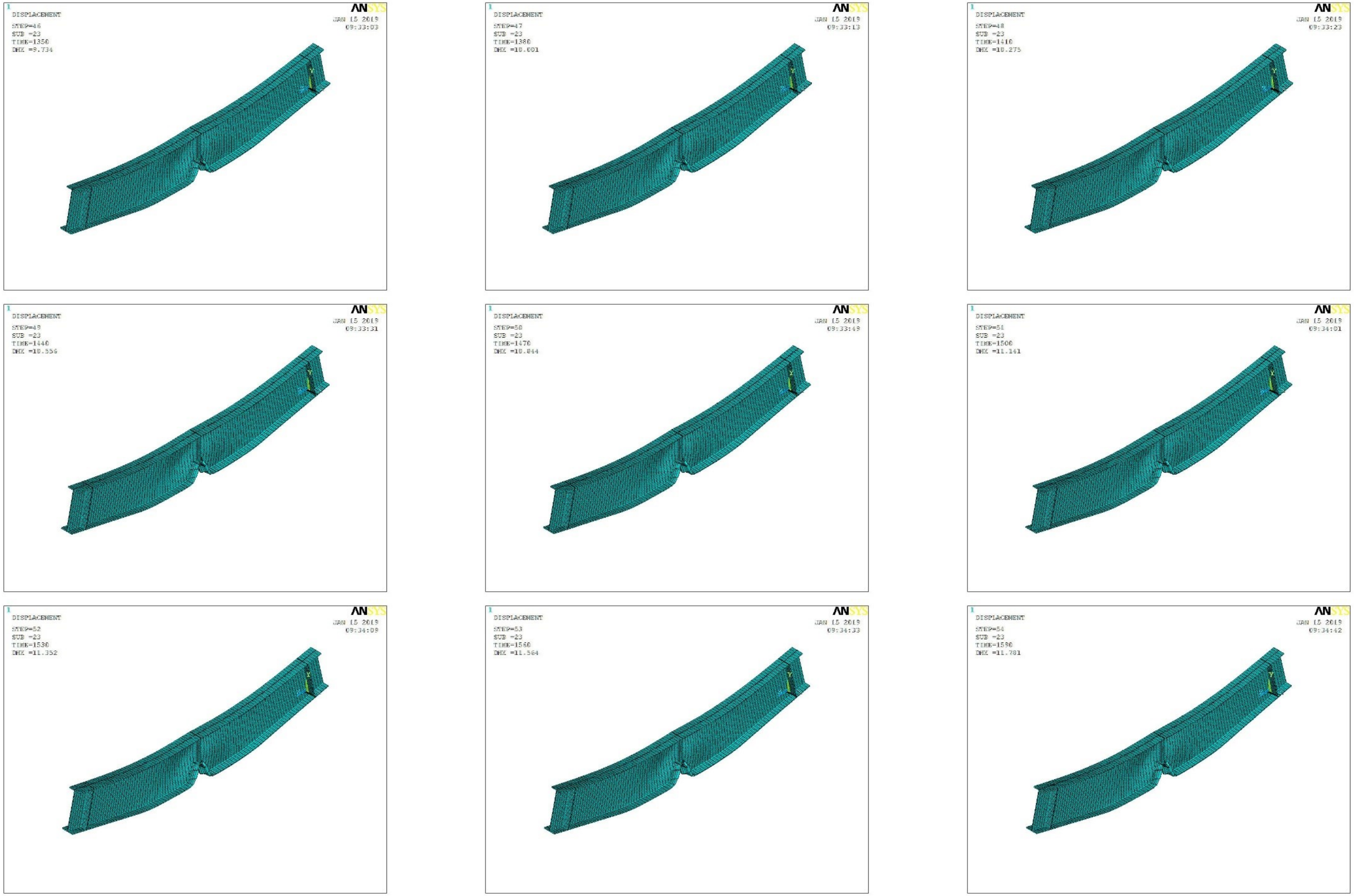

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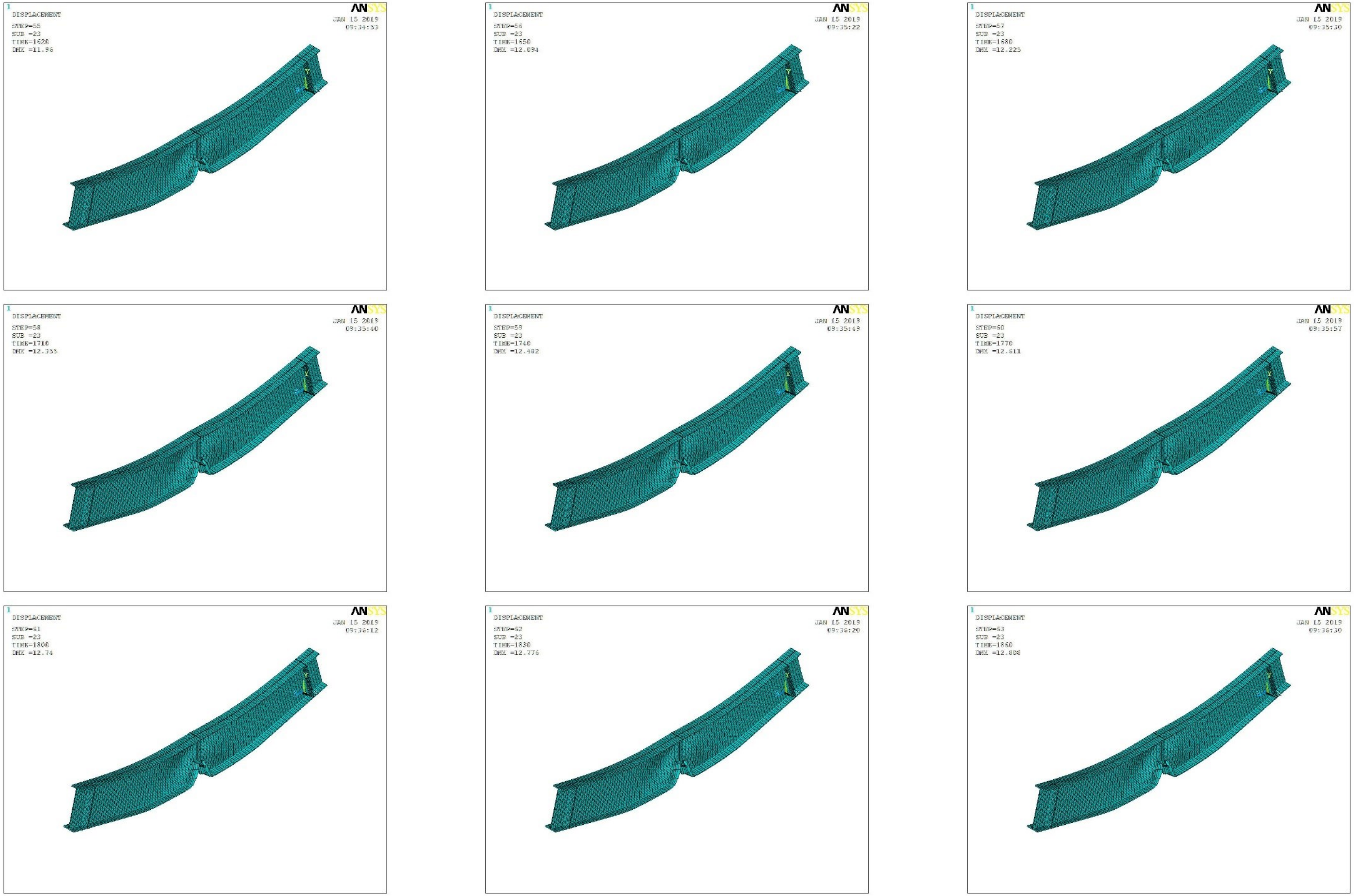

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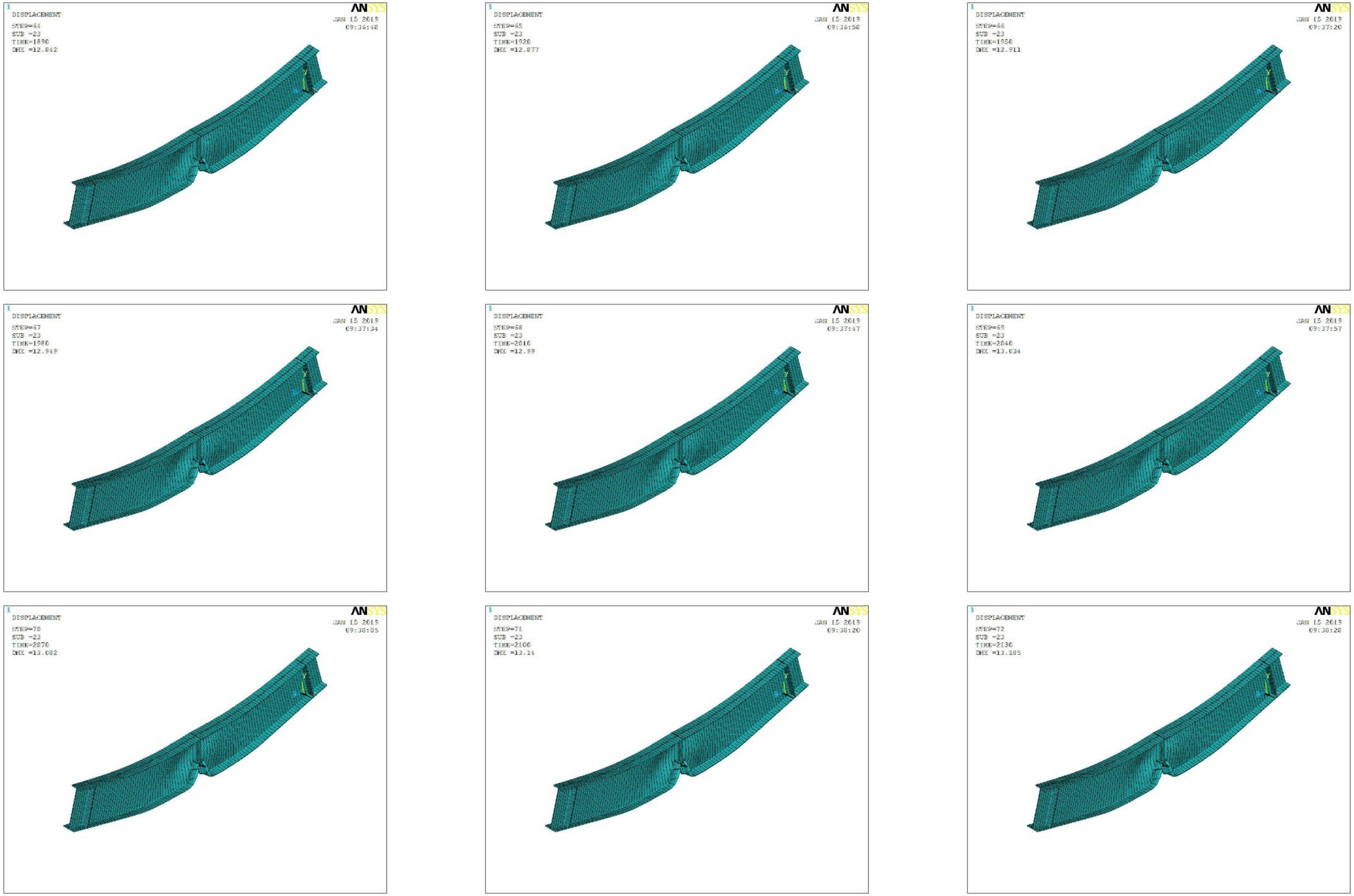

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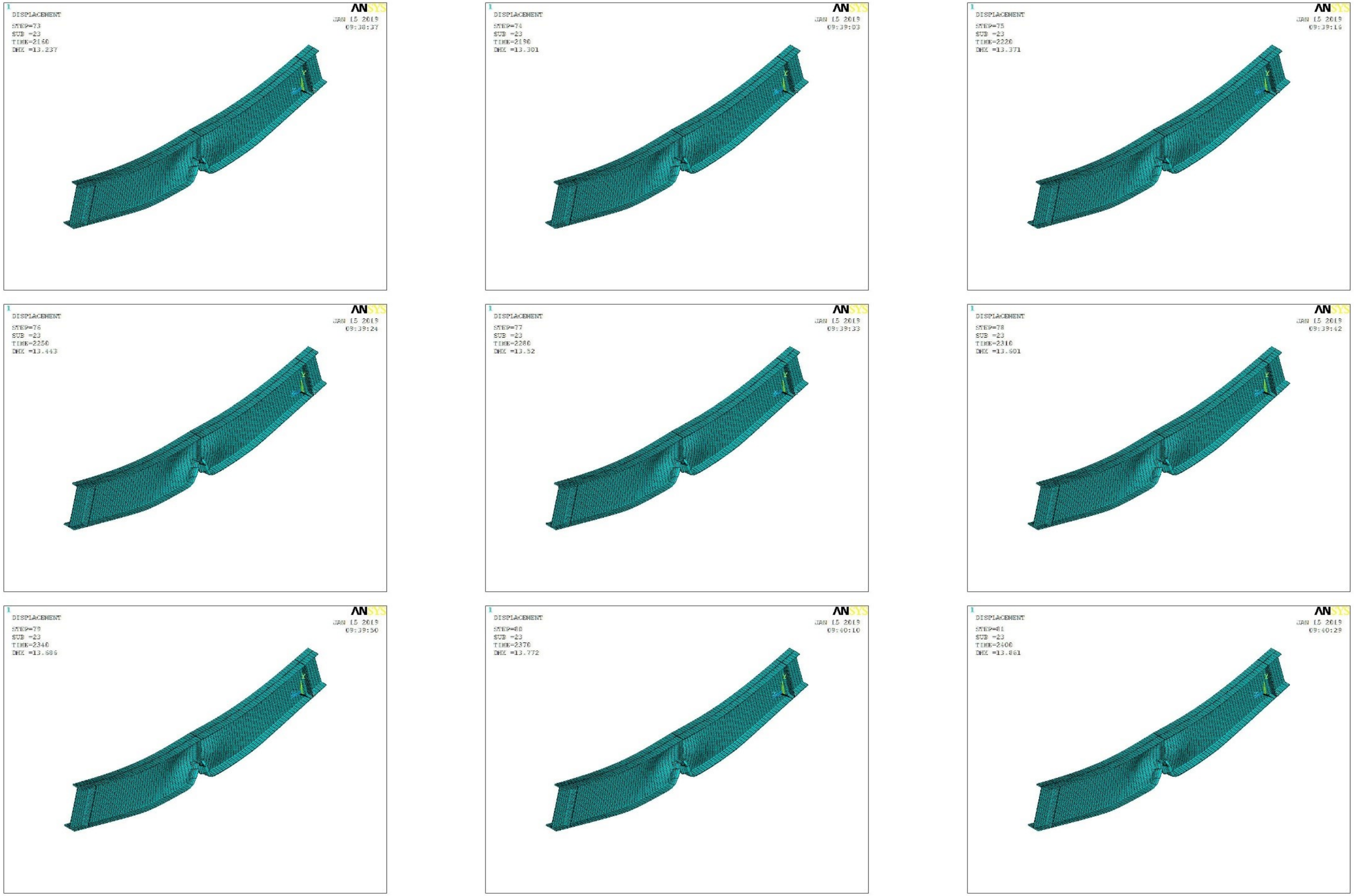

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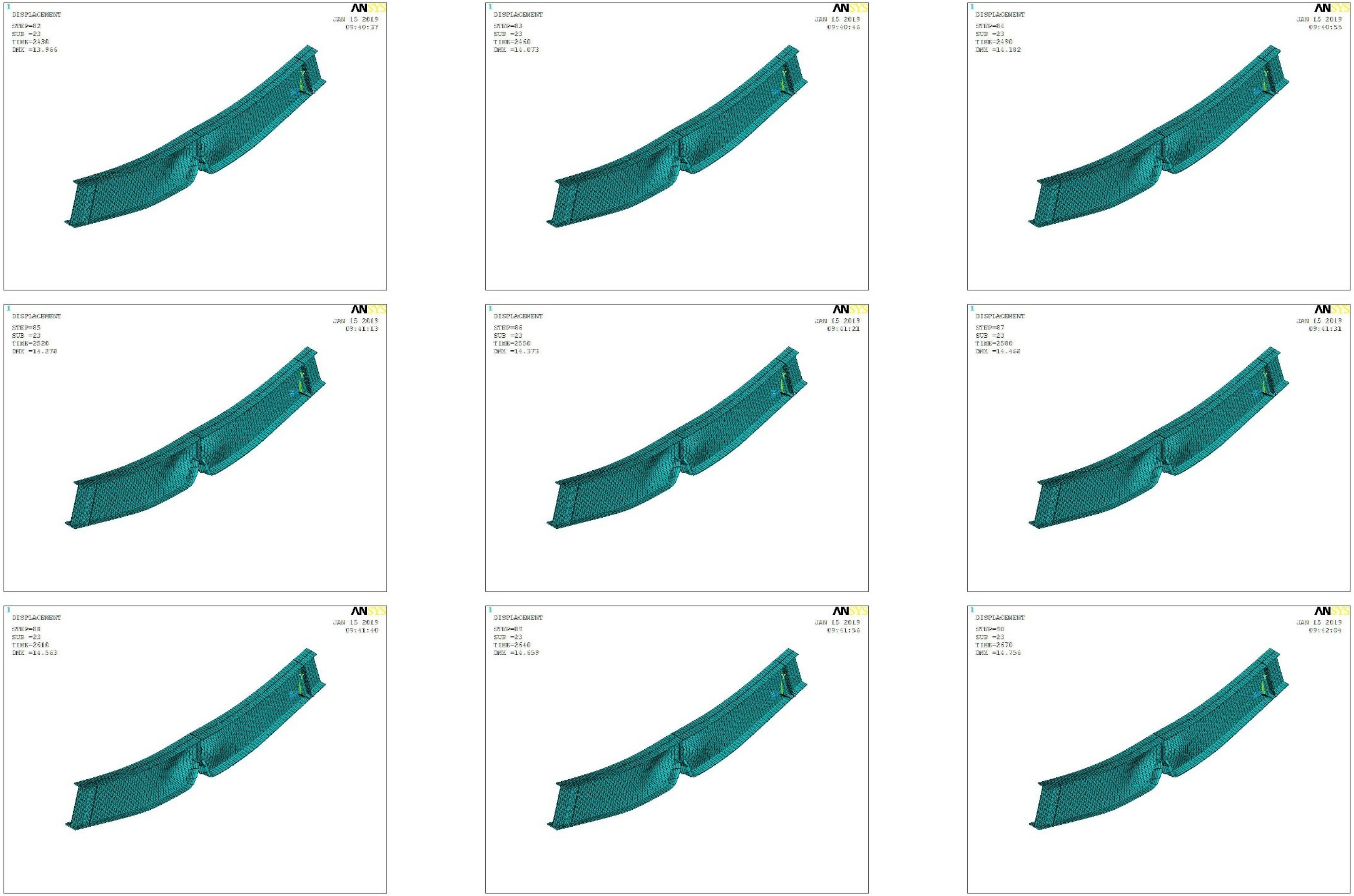

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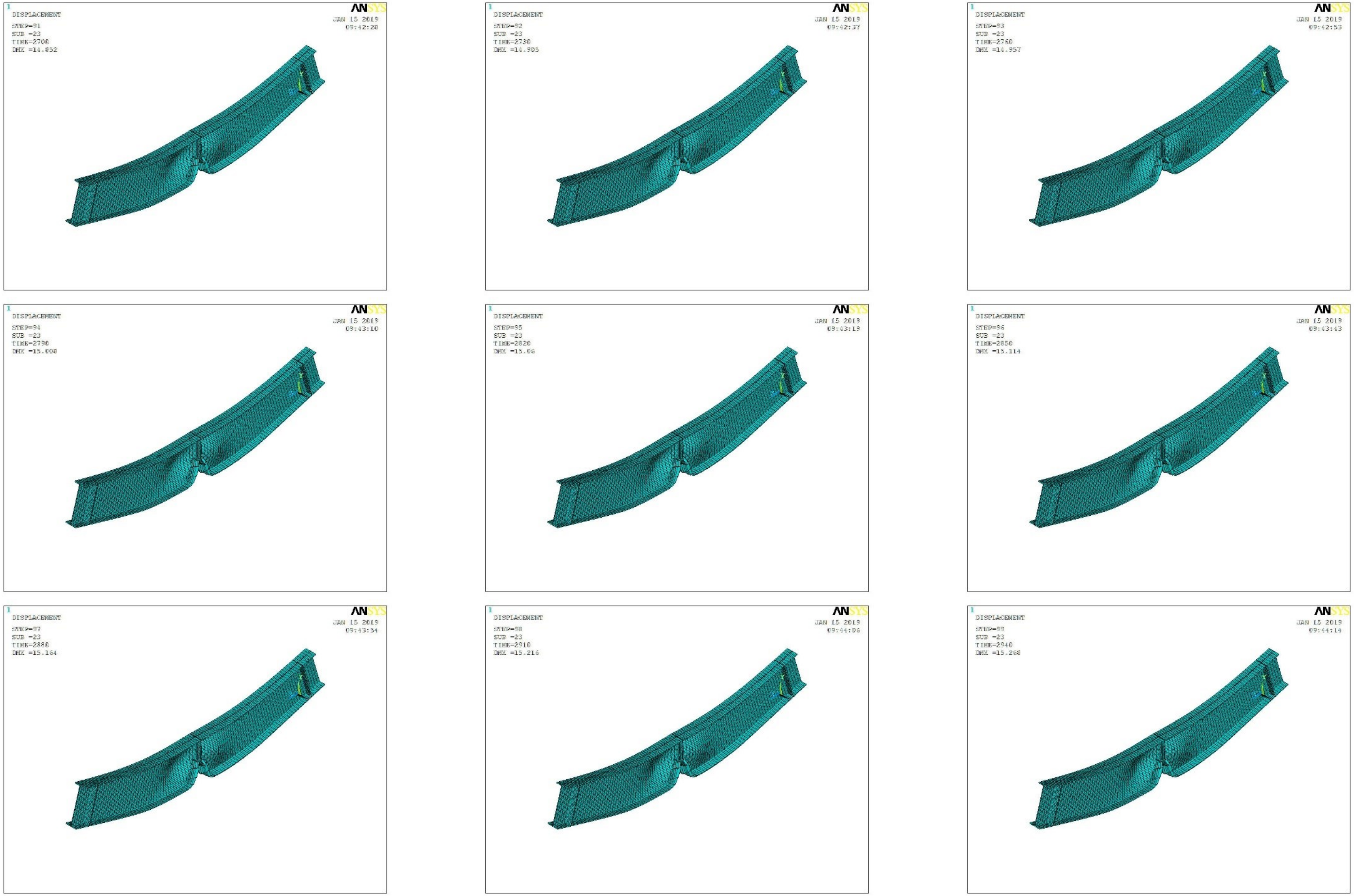

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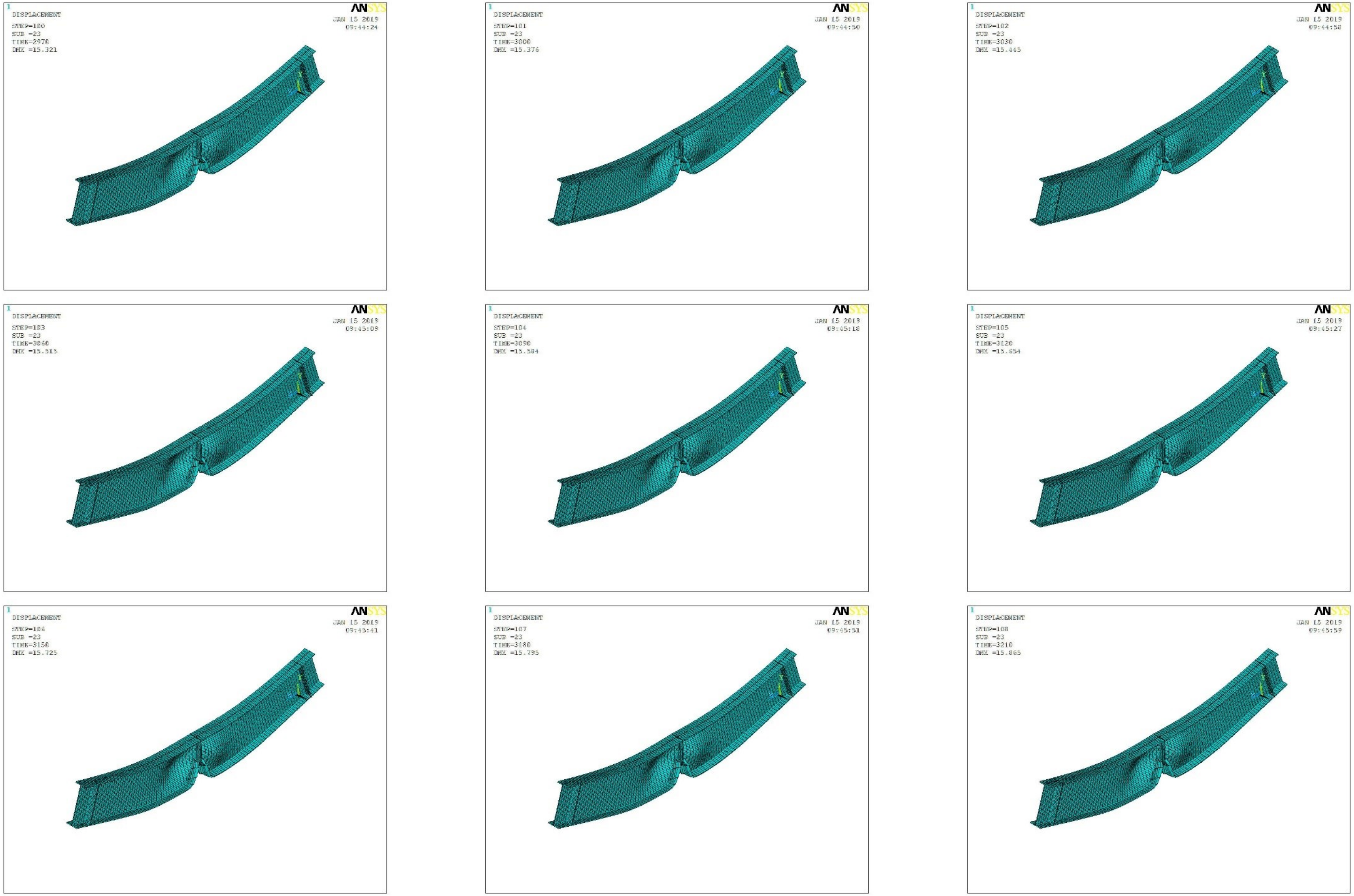

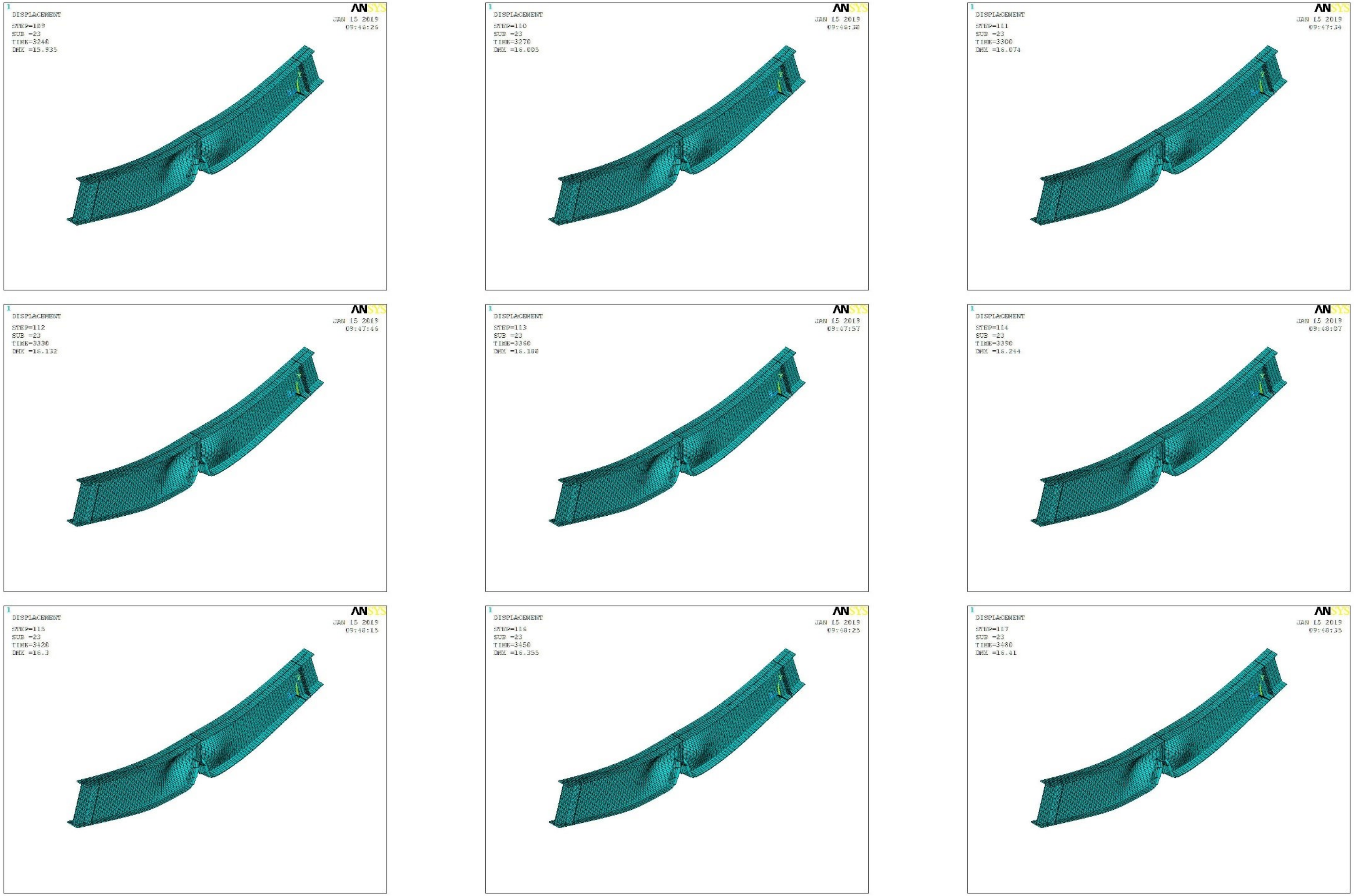
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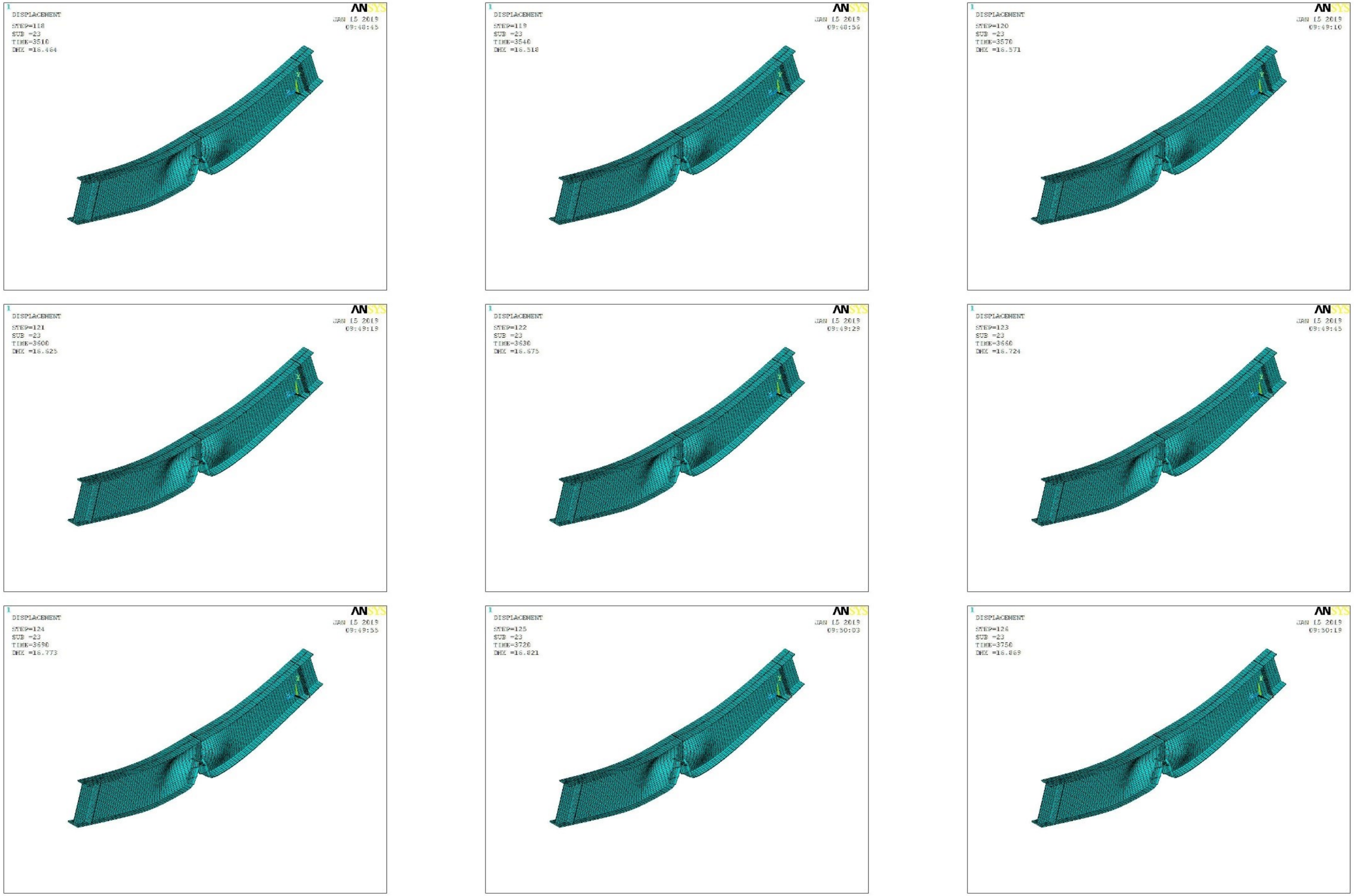

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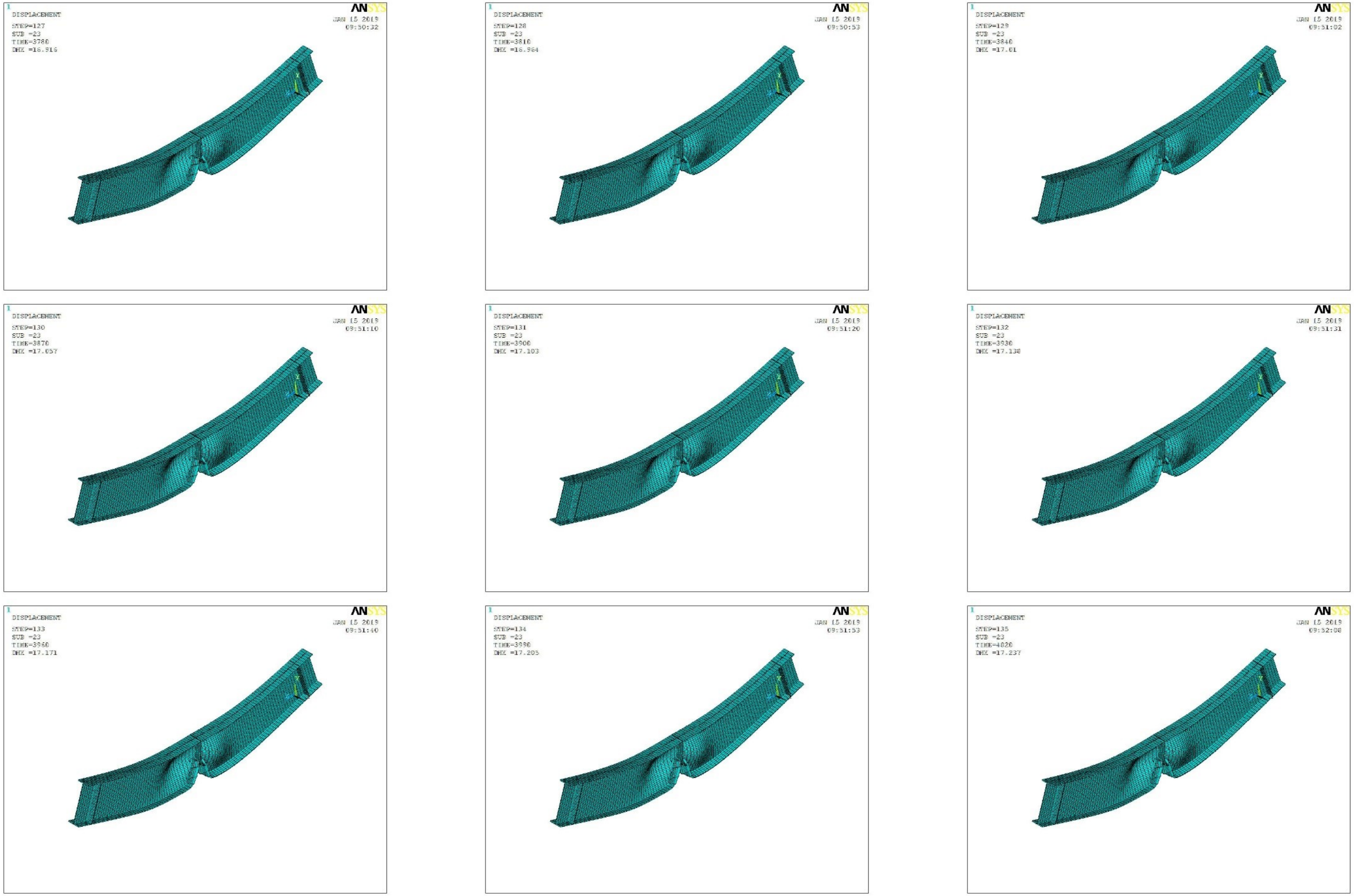

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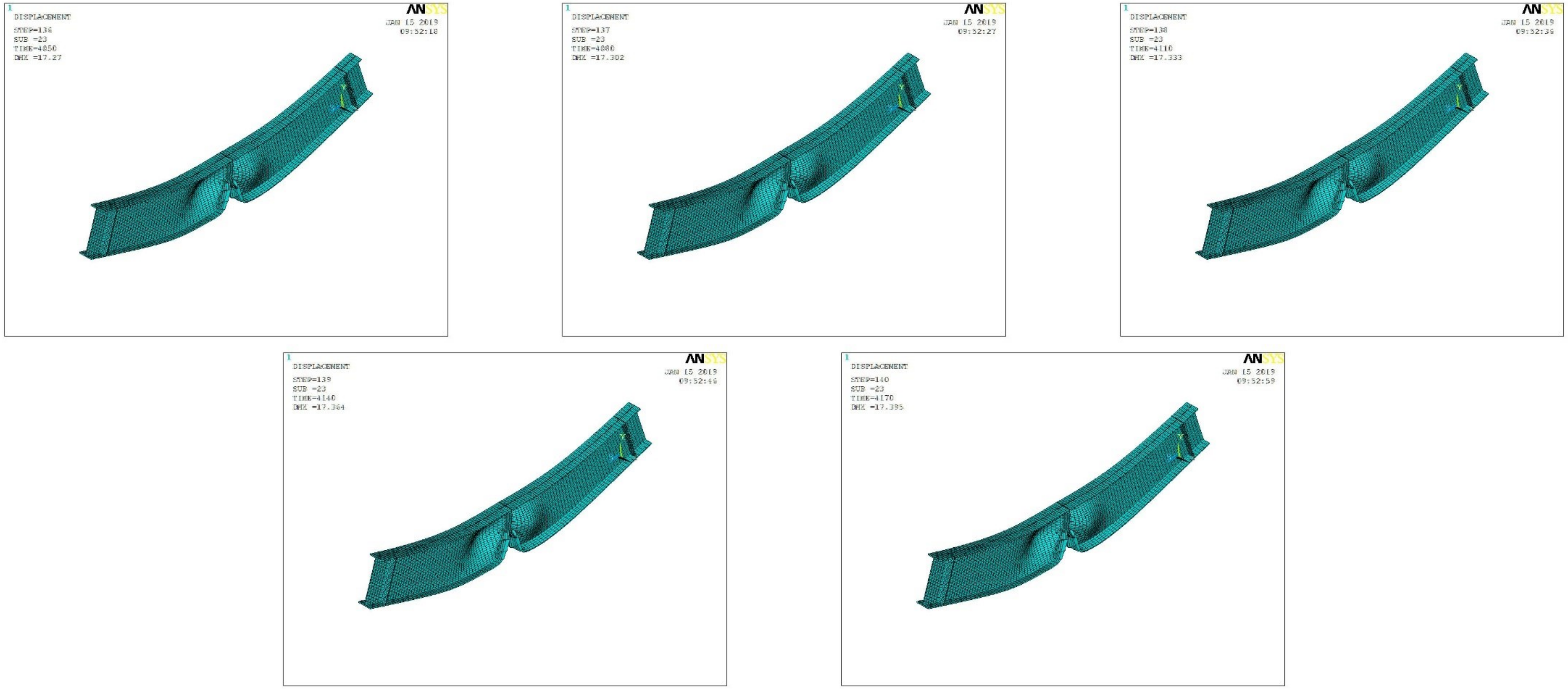

Fig. A1. Image collected to be used in benchmarking VC model for tracing temperature-induced instability (*Time* is displayed in seconds) – minor buckling occurs between 15-35 min, major buckling occurs between 35-65 min, and failure through buckling occurs between 65-70 min.