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Article

Digital Twin–Enabled Structural Health Monitoring and Lifecycle Optimization of Welded Heavy Equipment Assemblies Using Finite Element and Manufacturing Data Integration

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Abstract: Fatigue analysis and lifecycle management of welded heavy equipment assemblies are complicated by variable-amplitude loading, manufacturing-induced residual stresses, geometric discontinuities, and heterogeneous service environments. A digital twin–based SHM approach is technically appealing because it can integrate the as-built manufacturing data, finite element models, sensor data, inspection history and maintenance plans in an up-to-date engineering continuum. This review evaluates the suitability of digital twin concepts, welding simulation, finite element model updating, structural health monitoring and prognostic decision models for heavy duty welded booms, chassis and frames, lifting structures and other welded components for the assessment of fatigue and fracture. The literature reports methodological advances in isolated sub-problems including modelling of the heat source during the welding process, estimation of welding residual stress, local fatigue assessment, vibration-based monitoring and guided-wave inspection, Bayesian calibration, and remaining life prediction. However, there are few studies that complete the loop from manufacturing data to as-built structural state estimation to operational monitoring and lifecycle optimization. There are still considerable challenges in the model reduction process, the propagation of uncertainty due to variation in the weld process, traceable data architectures, defect-informed updating of meshes, testing of models under field loading and decision policies taking into account downtime, repair quality and inspection value. Future progress will require interoperable digital threads, physics-informed monitoring, probabilistic FE twins, and benchmark datasets representative of heavy-equipment assemblies (HEAs).
Keywords: Digital twin; welded structures; structural health monitoring; finite element model updating; fatigue prognosis

1. Introduction

Welded heavy equipment assemblies are a challenging category of engineering structures, offering the combination of high load transfer, geometric complexity, low production volume and long service exposure, typically in environments away from controlled laboratory conditions. These applications involve variable-amplitude loading, overload events, corrosion-assisted degradation, impact, repair-induced property changes, and weld-to-weld variability typical of welded structures encountered in excavator booms, loader arms, mining-truck frames, crane structures, agricultural-machine chassis, and other heavy-equipment applications. Although digital twin research has progressed rapidly in the manufacturing and asset management community, the problem of keeping a physics-consistent, inspection-informed and manufacturing-aware digital twin for welded heavy equipment has not advanced as quickly as other applications such as aerospace, civil infrastructure, and rotating machinery [1–4].

Structural health monitoring (SHM) provides a pathway for extracting damage-sensitive information from measured dynamic response, strain, acoustic emission, guided waves or inspection data. SHM should not be used as a substitute for structural mechanics. In the basic literature on SHM, it is shown that damage detection is comparative, is affected by operational and environmental variability, and relies on the selection of features, the quality of the baseline, and the choice of decision thresholds [5,6]. These problems are compounded by the local notch effects, metallurgical heterogeneity, residual stresses, distortion, undercuts, lack of fusion, porosity, and discontinuities in weld joints due to welding, particularly in heavy equipment assemblies. A digital twin for lifecycle optimization should therefore be based not only on SHM features and sensor data but also on finite element (FE) stress fields, weld process records, inspection evidence, and probabilistic fatigue or fracture models.

The application of finite element modelling is already a major part of the assessment of welded structures. Complementary estimates of temperature, distortion and residual stress are available from heat-source and thermo-mechanical welding simulations [7,8,35,36]. Structural-stress and local fatigue-assessment approaches are described in [9–11], whereas fracture-mechanics-based crack-growth assessment is supported by [29–32]. Manufacturing data are valuable because of the weld parameters, heat input, pass sequence, material used, fixture preparation, and inspection results which define the initial state of the structure. However, uncertainty remains in the measurement and simulation of residual stress, which deserves specific attention in fatigue-critical welded assemblies [12]. The digital twin challenge is not just to develop a geometrically detailed FE model; it is to keep a calibrated FE model that is uncertainty-aware and evolves with the addition of manufacturing, inspection, monitoring, and service data.

The literature's focus on digital twins has been on bidirectional data connection, the context of a digital twin during its lifecycle, and model updating, yet the implementation is more conceptual and platform level than it is in terms of mechanics associated with the weld [1,3,4]. The decisions involved in inspection intervals, derating, repair/reinforcement, component replacement and operational limits are required to optimize the lifecycle of a welded heavy equipment assembly. These decisions rely on the propagation of uncertainty in welding simulation and sensor interpretation to remaining useful life (RUL) and economic consequence. A rigorous basis for this problem is provided by the use of Bayesian calibration and probabilistic computer-model correction, although this approach is still not widely used in the context of heavy-equipment welded structures due to the lack of field data, high fidelity simulation costs, and lack of traceability between manufacturing and service records [13].

This review investigates the scientific underpinning for digital twin–based SHM of heavy equipment assemblies using FE models and manufacturing information. Peer-reviewed research in the fields of digital twins, welding simulation, welded-joint fatigue, residual-stress assessment, SHM, FE model updating, and prognostics are highlighted. The aim is to highlight technical maturity, weak integrations, and missing research directions to support the development of validated digital-twin tools for lifecycle optimization for welded heavy equipment assemblies.

2. Literature Review

The evidence base related to welded heavy equipment is spread across several communities, within the overarching framework of digital twin research. Tao et al. defined the digital twin as a digital representation that is connected to data throughout the product life cycle, extending the product information to become a resource that can be reused continuously throughout the product's lifecycle, beyond the use of design information [14,15]. Subsequent reviews made it clear that the label "digital twin" is applied with varying degrees of granularity and specificity, from static digital models to digital shadows that are updated in real time to "closed-loop decision systems" [3,4]. This distinction is not merely semantic for welded heavy equipment. If manufacturing and service data can update model states, uncertainties, and decision variables, then a static FE model can evolve into an updateable lifecycle optimization twin. While modelling-focused reviews focus on the fidelity management, uncertainty handling, and computability of twins, the lifecycle framing proposed by Grieves and Vickers is still useful because it emphasizes the need for traceability through conceptual design, production, use and retirement [16].

A substantial body of manufacturing literature addresses digital twins, but comparatively little work addresses weld-specific structural mechanics. Stark et al. have presented twinning development and operation of technical systems and services, highlighting the shift from the design-time models to the operation-time representations [18]. This transition is especially challenging for welded assemblies since the nominal design state is materially different from the as-built state. Fatigue behaviour may be controlled by weld bead geometry, misalignment, properties of the heat-affected zone, residual stresses, distortion and repair history. Accordingly, a useful twin needs to include manufacturing records in the FE model prior to operational monitoring. The data architecture logic is provided by studies on digital twin-based product lifecycle management and smart manufacturing [14,15,40] but they seldom explain how to represent weld defects, residual stress, and local fatigue models in a computationally tractable digital twin.

Finite element model updating is a mature technology that spans the gap between nominal models and measured structures. It has been demonstrated in classical surveys and monographs that the stiffness, mass, damping, boundary condition and uncertain parameters can be updated by using modal or response data [19,20]. The welded heavy equipment problem is more difficult since the parameters that cause the damage are local and the responses that are measured are global. Changes in natural frequency can signify stiffness changes, but early cracking in a weld toe in a large frame may cause response changes that are not distinguishable. This limitation has been known in the early damage localization based on frequency [21] and is still a key point in the vibration-based SHM [22]. In the case of monitoring civil infrastructure, Brownjohn's review indicated that such long-term monitoring must be done carefully to distinguish between effects of damage and temperature, humidity, traffic, and variations in boundary conditions [23]. Other factors that may be considered equivalent in heavy equipment are payload variation, soil-tool interaction, hydraulic actuation, operator behaviour, and changing support conditions.

These issues are partially addressed by data-driven SHM techniques, which learn operational variability and damage-sensitive features. For SHM, cointegration has been employed to eliminate environmental trends [24] and comparative machine-learning studies indicated that the novelty detection and novelty classification performance is quite dependent on the availability of representative baseline data [25]. These findings are relevant to the heavy equipment industry, as labelled crack-growth data from field assemblies are limited and costly to obtain. There are trade-offs in sensor technologies as well. The use of piezo wafers or guided waves can interrogate areas of potential damage of interest [26,27] and the literature on smart sensors reveals that other techniques of interest (acoustic, vibration, strain, ultrasonic) have varying advantages in terms of coverage, sensitivity and installation requirements [28]. It is therefore essential for a digital twin architecture to recognize that the measurements obtained from SHM are not a single damage indicator but rather heterogeneous evidence with known blind spots.

There is literature available regarding welded joint fatigue that provides the basis for understanding the damage mechanics of the sensor evidence. The fracture-mechanics approach of Paris and Erdogan for relating stress-intensity-factor range to fatigue crack growth [29] and the Newman–Raju stress-intensity-factor solution for semi-elliptical surface cracks in finite plates [30] are still relevant. Ritchie's mechanistic review showed that crack-growth behaviour is influenced by closure, microstructure, environment and loading regime [31] and Suresh's monograph is an important presentation of fatigue mechanisms and crack propagation [32]. In welded structures, the fatigue behaviour can frequently be more dependent on notch severity and quality of the welds than on nominal material strength. Local-approach fatigue assessment and structural-stress methods were developed to decrease the dependence on hot-spot stresses, especially those dependent on mesh and to more accurately represent the behaviour at the weld toe and root [9–11]. Although many fatigue assessments simplify multiaxial loading, heavy equipment welds are still subjected to combined bending, torsion, axial, and local attachment loads [33].

The welding simulation literature is fundamental because the digital twins have to be set up starting from the as-built condition. The double-ellipsoidal heat-source model is still commonly used for FE representation of heat input for arc-welding and is referred to as Goldak's model [7]. In Lindgren's review of welding simulation, the thermal, metallurgical and mechanical coupling of the predictive modelling was highlighted, but he cautioned that complexity is quickly added with the addition of phase transformation, plasticity, creep and multi-pass sequencing [8]. Residual stress is especially problematic since it is a function of heat input, restraint, pass order, material response, and post-weld treatment. Diffraction, hole drilling, sectioning, and contour mapping are some of the residual-stress measurement techniques used to help validate the process, each with resolution and destructive limitations [12,34]. Simulations of multi-pass welding have demonstrated that calculated temperature and residual-stress fields can be compared with experimental measurements, however, calibration remains problem-specific [35]. Welding models are also shown to be physically rich and computationally costly for full assembly-scale lifecycle twins in computational welding mechanics textbooks [36].

The decision layer is provided by the prognostics and maintenance literature. Condition-based maintenance requires degradation-state estimation, degradation-state prediction and action selection under uncertainty [37]. Data-driven, physics-based and hybrid approaches to statistical RUL estimation are distinguished and the selection depends on the observability of degradation and the availability of failure data along with the adequacy of the model [38]. Welded heavy equipment assemblies do not often generate the large amounts of "run-to-failure" data needed for "pure" data-based models. Thus, hybrid twins are more consistent with the domain: FE and fracture mechanics limit extrapolation and monitoring and inspection data feed into the state. In the field of cyber-physical manufacturing architecture studies, computer-generated data and analysis can be applied in industrial environments [39]; however, the optimization of the structure's lifecycle also needs a mechanics-based consequence evaluation.

Table 1. Representative peer-reviewed studies relevant to digital twin–enabled SHM of welded heavy equipment assemblies

Ref.	Study focus	Materials/methods/system/model used	Key contribution	Limitation or research gap	Relevance to welded heavy equipment
[1]	Digital twin state of the art	Industrial digital twin framework	Clarified industrial twin elements and lifecycle data connection	Limited weld-specific mechanics	Supports overall lifecycle architecture
[2]	Structural digital twin for life prediction	Aircraft structural life prediction framework	Connected structural models with individual asset life prediction	Aerospace-focused; not weld-manufacturing specific	Demonstrates asset-specific structural prognosis logic
[3]	Digital twin classification	Systematic review of twin definitions and characteristics	Distinguished levels of digital model, shadow, and twin	Does not resolve structural fatigue implementation	Helps prevent overuse of “digital twin” terminology
[7]	Welding heat-source FE	Double-ellipsoidal heat-source model	Enabled practical arc-welding thermal simulation	Requires calibration; process-specific	Foundation for weld thermal history and residual-stress estimation
[8]	Welding simulation complexity	Coupled thermal-mechanical FE review	Identified modelling complexity in welding FE	Full assembly simulation can be expensive	Defines fidelity limits for weld-aware twins
[11]	Weld fatigue stress parameter	Structural stress definition and numerical implementation	Reduced mesh sensitivity in welded-joint fatigue assessment	Requires careful extraction and validation	Useful for FE-based fatigue modules
[12]	Residual stress measurement	Review of measurement techniques	Compared residual-stress measurement principles	Measurement coverage and destructiveness vary	Supports validation of as-built residual-stress state

[13]	Bayesian calibration	Probabilistic computer-model calibration	Formalized calibration and model discrepancy	Computationally demanding in high-dimensional FE	Basis for uncertainty-aware model updating
[19]	FE model updating	Structural dynamics model-updating survey	Established updating concepts and limitations	Global response may miss local weld cracking	Supports twin calibration from measured response
[23]	Long-term SHM	Civil infrastructure monitoring review	Emphasized operational/environmental variability	Civil structures differ from mobile heavy equipment	Relevant to field variability and monitoring drift
[24]	Environmental trend removal	Cointegration for SHM data	Reduced confounding operational trends	Requires stable statistical relationships	Applicable to temperature/load variability compensation
[25]	ML-based damage detection	Comparative SHM machine learning	Showed algorithm sensitivity under variability	Label scarcity remains problematic	Supports cautious use of data-driven monitoring
[26]	Piezoelectric SHM	Piezoelectric wafer active sensors	Local guided-wave sensing foundation	Installation and coupling affect performance	Useful for weld-critical hot spots
[29]	Fatigue crack growth	Crack-growth law	Established stress-intensity-based crack propagation	Does not address weld complexity alone	Core propagation model for detected cracks
[35]	Multi-pass weld residual stress	Thermo-mechanical FE and experimental comparison	Demonstrated weld residual-stress simulation and validation	Case-specific calibration	Supports as-built weld-state modelling

Table 1 lists and summarizes representative, peer-reviewed studies across the five digital twin, welding FE, SHM, fatigue, and prognostic domains. Digital twin papers focus on lifecycle integration and data connection, FE papers on manufacturing induced state variables, SHM papers on in-service feature extraction and fatigue papers on propagation of damage. There are few peer-reviewed publications that fully incorporate weld process records, FE models based on weld residual stresses, sensor-measured crack state, and a maintenance optimization for a heavy equipment assembly. This gap explains why digital twins are often described as promising for welded structures but are not yet commonly validated under field loading and repair conditions.

There are two technical tensions: First, high fidelity welding simulation is costly, and local fatigue models are detailed and need to be updated during operational twins. This implies that reduced-order modelling, surrogate correction, and adaptive fidelity selection are required but should not override local weld-toe or weld-root effects controlling fatigue. Second, there is a lot of data, but not much damage labelling. Although model discrepancy can be reduced by using a physics-informed updating, it is important to explicitly represent model discrepancy, otherwise the twin could look accurate, but it may contain uncertainty in the weld geometry, as well as residual stress, boundary conditions, or probability of detection. These issues motivate a lifecycle architecture that sees digital-thread traceability and probabilistic model updating as structural integrity requirements, not software convenience.

3. Methodology

The review was arranged in the form of a critical technical analysis of the peer reviewed journal papers and books dealing with digital twin–based SHM of heavy equipment assemblies welded together. The scope of literature included both basic and recent work from 1963 to 2025, since the topic is based on the well-developed theory of fracture mechanics and more recently on digital twin architectures. The search logic adopted was based on the combination of terms associated with digital twins, structural monitoring, welded structures, finite element modelling, residual stress, manufacturing data, fatigue assessment, fracture mechanics, model updating, Bayesian calibration, prognostics and lifecycle optimization. Search strings that were representative of the search included: “digital twin structural health monitoring welded structures”, “finite element model updating fatigue welded joints”, “welding simulation residual stress finite element”, “manufacturing data digital twin lifecycle”, “structural stress fatigue welded joints”, “guided waves weld crack monitoring”, “Bayesian calibration finite element structural health monitoring”, and “remaining useful life fatigue crack growth welded structures”. Peer reviewed journals and books in academic publications (IEEE Xplore, Science Direct, Springer Link, Wiley Online Library, Cambridge University Press, discipline–specific journal archives) were preferred.

The following five specific technical blocks were considered to have a direct relation with the studies: digital twin architecture, FE model updating, welding process/fracture simulation, welded-joint fatigue/fracture assessment, and SHM/prognostics. The evidence from different article types was not treated as interchangeable. Digital twin papers were analysed for lifecycle connectivity, state updating and model-management logic. Welding simulation studies were assessed for heat-source modelling, thermo-mechanical coupling, residual-stress prediction, and validation requirements. The following criteria were used to assess the SHM studies: sensor modality, robustness of features, operational variability and damage localization control. The fatigue and fracture literature was evaluated for its ability to convert stress histories, weld geometry, and crack-size data into life predictions. Prognostics literature was reviewed for degradation-state estimation, uncertainty treatment, and decision support. No citations were made from websites, non-peer reviewed reports, preprints, vendor documents and grey literature.

A wide range of methodological approaches used in the reviewed studies exist. Digital twin research employs conceptual lifecycle architectures, data models and architectures of integrating digital twins into manufacturing services [1,3,4,14,15,17,18,40]. These studies are helpful in understanding the intent of data flow and data lifecycle, but they are not always able to focus on the specifics of damage mechanisms in the weld. The modelling of the welding process by simulation is based on a transient thermal analysis, heat-source calibration, assessment of the elastoplastic stress state and might include a modelling of the metallurgical transformation [7,8,35,36]. They are employed to estimate state variables in the as-built case but are expensive and sensitive to parameters and cannot be applied directly when creating real-time twins. The following approaches are adopted in weld fatigue studies: nominal-stress, structural-stress, notch-stress, strain-life and fracture-mechanics approaches [9–11,29–33,41]. These methods are well-developed methods for assessment, but need stress histories, weld-detail classification, local geometry and crack-state information which can be ambiguous in field assemblies.

SHM techniques include vibration, strain, acoustic emission, guided waves, and machine-learning techniques [5,6,21–28]. Vibration based techniques can be used to determine the stiffness change throughout the system but are not likely to detect early weld toe cracking. Local piezoelectric sensing and guided waves have higher sensitivity in the area of the selected weld, but are sensitive to path modelling, coupling conditions, and environmental compensation. Labelled data can be utilized to improve weld damage classification with machine learning methods, but field labelled weld damage is rare, which promotes the use of hybrid methods. The mathematical methods that can be used to couple FE models and measurements are model updating methods [13,19,20] and the decision framework is condition-based maintenance and RUL studies [37,38].

A short evidence coding process was used to code the tables and figures. The selected sources were manually coded as belonging to one or more of the following lifecycle phases: manufacturing-state initialization, baseline FE modelling, monitoring, state estimation, damage prognosis, and maintenance decision support. The coding was not a prevalence analysis as a bibliometric analysis but was undertaken to reveal the transparency of the technical relationships (which are well established and which are not) of the selected peer-reviewed corpus. The data presented in Figures 1-4 do not represent the volume of publications worldwide but rather come from this coded review corpus. These figures do not represent fatigue lives, failure rates in the field or rates of industrial use but represent the number of source citations recorded for this review.

This methodology was selected because this is an integrative problem and there is no single experimental protocol that can control this problem. Conventional meta-analysis is not suitable as reviewed papers differ in number of structural scales, loadings, material, sensor type, level of fidelity in the FE, weld process and validation metrics. A narrative-critical method enables technical assumptions of each domain to be compared without having to pool together incompatible performance measures. The principal limitations are potential source-selection bias and possible errors arising from manual coding. The discussion is split up into the mature subdomain evidence and the cross domain integration issues, which have not yet been resolved, to stay clear of overinterpretation.

4. Discussion

The literature reviewed shows that, at present, the use of a digital twin to optimize the lifecycle of welded heavy equipment assemblies (HEAs) can only be realized if four layers of models are maintained as a separate, but connected, set: manufacturing-state model, structural-analysis model, monitoring model, and decision model. These layers often are conflated in conceptual twin proposals. If weld-induced residual stresses, local weld geometry, defect states and uncertainty in load transfer are not present, the geometric model with the live sensor dashboards is not a structural integrity twin. On the other hand, a comprehensive welding FE model is of little value in terms of lifecycle unless it can be populated with monitoring and inspection data. Table 2 makes this distinction more explicit by correlating data classes with twin functions. The best present evidence can be found for specific combinations like welding parameters to calibration of thermal FE [7,8,35,36], vibration features to damage detection [5,21–25] or crack size to prognosis of fracture mechanics [29–32]. The least robust evidence relates to the chain of evidence from the weld process record to the residual stress field, to the initiation of fatigue cracks, to the observation of their progression by sensors, to the optimization of maintenance.

Table 2. Data assets and their roles in a welded-assembly digital twin

Data asset	Typical source	Primary twin function	Mechanically useful output	Key uncertainty	Supporting references
Weld process records	Welding controller, WPS, operator logs	Manufacturing-state initialization	Heat-input class, pass history, process traceability	Missing or inconsistent metadata	[7,8,14,15,35,36]
Bead geometry and distortion	Laser scan, structured light, inspection	FE geometry correction	Toe profile, misalignment, distortion field	Registration to mesh	[8–11,36]
Residual-stress evidence	Diffraction, contour method, hole drilling, FE simulation	As-built stress-state calibration	Residual-stress prior or field	Spatial coverage and relaxation	[12,34,35]
FE stress/strain fields	Global FE and local submodels	Load transfer and fatigue assessment	Hot-spot, structural, notch, or crack-driving stress	Boundary conditions and mesh sensitivity	[9–11,19,20]
Operational loads	Strain, pressure, acceleration, duty cycle logs	Load reconstruction	Variable-amplitude stress histories	Sensor placement and load-path uncertainty	[5,6,22,23,37]

SHM features	Vibration, guided waves, acoustic emission	Damage detection and localization	Damage index, feature residual, event cluster	Environmental and operational variability	[21–28]
Inspection crack data	NDT, visual inspection, phased array, repair reports	Crack-state updating	Crack size, location, confidence	Probability of detection and sizing error	[29–32,37,38]
Maintenance records	CMMS, service reports, repair logs	Lifecycle decision updating	Repair state, downtime, altered geometry	Repair quality and documentation	[37,38,40]

This is highlighted in the chronological distribution in Figure 1, as there is a structural explanation behind this gap. Fatigue and fracture mechanics studies did not develop in the same era nor in the same culture of validation as did welding FE, SHM and digital twin studies. So, integration is not just a software chore. It must have consistent state variables for all domains. For instance, if a weld heat-input record is available, it can be used to estimate the residual stress; but the residual stress must be converted to the stress-ratio and crack-driving-force terms of fracture mechanics. Likewise, if a guided-wave damage index is to be used to affect an FE model or RUL estimate, it should be related to the crack geometry or stiffness degradation.

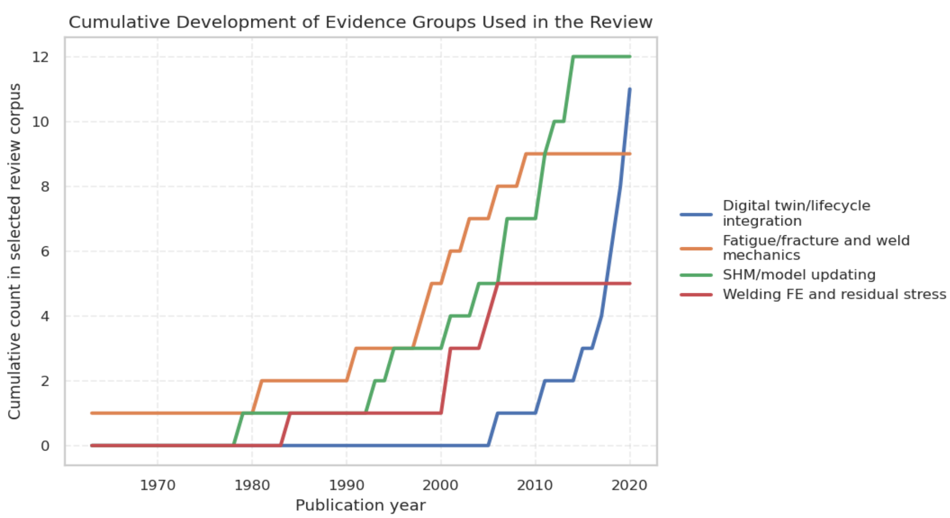

Figure 1. Chronological distribution of selected peer-reviewed sources by evidence group

Data integration is the least exploited opportunity in manufacturing. HEAs typically keep weld procedure specifications, log of the robot or the operator, certificates of materials, inspection reports and repair records, but these are not generally brought into analysis-ready state variables. Residual stress and distortion are affected by heat input, speed of travel, sequence of passes, restraint, preheat, temperature and weld bead geometry, but material constitutive data, thermal boundary conditions, and evidence of calibration for every production weld may not be available for high fidelity welding simulations [7,8,35,36]. A pragmatic digital twin should therefore not be stuck between no consideration of manufacturing variability and providing complete thermo-metallurgical FE simulation for each weld. It is more defensible to use a tiered approach where critical welds can be detailed in a welding simulation or by performing a measurement-based calibration and lower-criticality welds can be represented by uncertainty bounds based on process class, inspection quality and structural consequence. See Table 3.

Table 3. Model classes for digital twin–enabled lifecycle optimization of welded heavy equipment assemblies

Model class	Main inputs	Outputs	Strength	Limitation	Best lifecycle use
Thermo-mechanical welding FE	Heat source, pass sequence, material data, restraint	Temperature, distortion, residual stress	Captures manufacturing-induced state	High calibration and computational cost	Critical weld initialization
Global structural FE	Geometry, loads, boundary conditions	Assembly stress, strain, stiffness, modal response	Captures load paths	May miss local weld toe effects	Fleet-level stress reconstruction
Local weld submodel	Weld geometry, local mesh, structural stress boundary conditions	Notch or local stress metrics	Represents weld-critical details	Sensitive to geometry and modelling assumptions	Critical detail ranking
Structural-stress fatigue model	FE nodal forces/stresses, thickness, weld line	Mesh-robust fatigue parameter	Practical for complex welded joints	Requires validated extraction procedure	Design screening and service stress conversion
Fracture-mechanics model	Crack size, stress intensity, stress history, growth parameters	Crack growth and RUL	Mechanically interpretable after detection	Requires crack geometry and growth-law uncertainty	Post-detection prognosis
Bayesian updating model	Prior parameters, measurements, model discrepancy	Posterior state and uncertainty	Integrates data and physics	Computational cost and identifiability issues	Twin calibration and decision confidence
Data-driven SHM model	Sensor features, baseline data, labels if available	Novelty score or class label	Useful under complex signal patterns	Weak extrapolation outside training data	Screening and anomaly detection
Maintenance decision model	RUL distribution, inspection cost, downtime, repair options	Inspection or repair policy	Converts prognosis into action	Requires cost and risk models	Lifecycle optimization

Residual stress is a central example of why uncertainty must be made explicit. While measurement methods are useful, they will not give all of the information. Diffraction methods can give local stress information, contour methods can be used to map a cut plane, and destructive or semi-destructive methods may not be feasible when dealing with a production assembly [12,34]. Although simulation can be used to estimate residual stress fields, it is highly dependent on the calibration of the heat-source, material data, phase transformations, clamping and pass sequence [8,35,36]. When treated as deterministic, the twin can underestimate the uncertainty of crack-driving-forces. If this problem is not considered, local fatigue estimates may be non-conservative or overly conservative depending on weld treatment, stress relief, mean stress and crack closure. The evidence presented here shows that there is a good basis for using the residual stress as a probabilistic state field, not a single correction.

Finite element model updating is a necessary but partial solution to the problem of making analytical and measured behaviour agree. Global modal updating can be used to correct stiffness distributions and boundary conditions [19,20]; however, many times damage to welded heavy equipment has been observed to start from small local stress concentrations. Thus, the detectability problem is scale dependent. A crack at a weld toe can be a significant stress concentrator and affect the structure even before a measurable change in low order global modes is seen. Vibration monitoring is more suited for global degradation/loosening or significant loss of stiffness, while local strain, guided-wave, and acoustic methods are more suited for early weld cracking [22,26–28]. In Figure 2, each data stream is actually used for two different twin functions, and none of the data streams is uniquely used for all four functions.

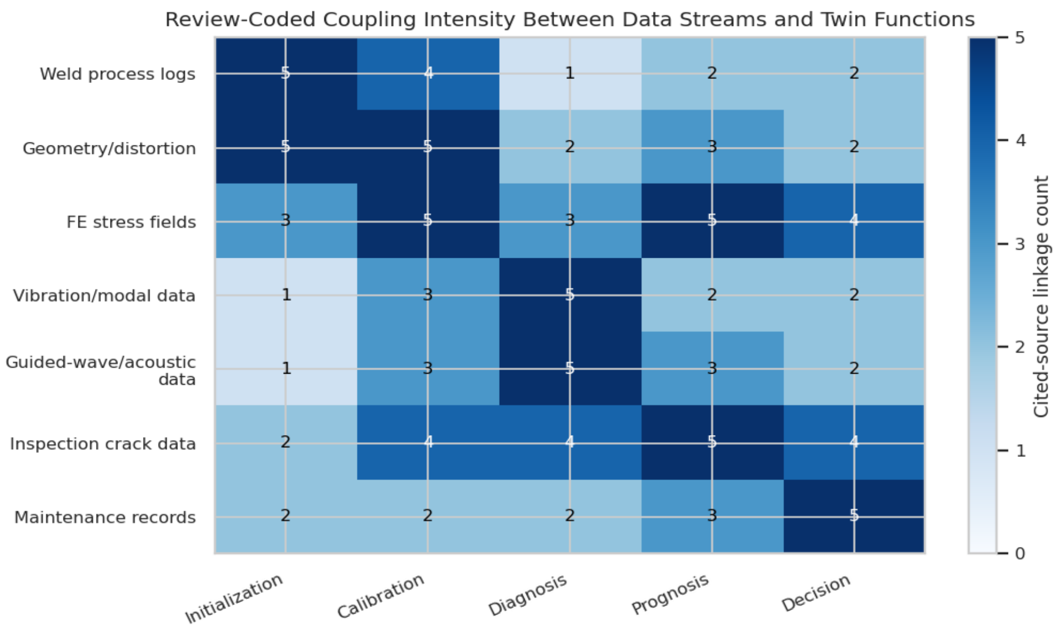

Figure 2. Review-coded coupling intensity between data streams and digital twin functions

The best digital twin architecture will probably be hybrid. The pure data-driven approach to SHM is limited with a small number of labelled failures in heavy equipment. A purely physics-based analysis is limited by uncertain loads, weld geometry, residual stress and repair history. A hybrid approach should use FE models and fracture mechanics to limit extrapolation, while sensors and inspections update state estimates. Bayesian calibration is especially relevant as it separates the parameter uncertainty from the observation error and model discrepancy [13]. For welded heavy equipment, discrepancies should not be thought of as statistical add-on items. They can be the missing weld misalignment, incorrect load paths, missing local plasticity, unknown residual stress relaxation or incorrect boundary conditions. Without discrepancy modelling, updating could force physically meaningful parameters to compensate for missing mechanisms.

Fatigue prognosis is the scientific backbone of lifecycle optimization and should remain the focus. There are various differences between welded-joint fatigue methods in terms of geometry and data quality. On the other hand, nominal-stress approaches are simple to compute but inadequate in representing complex loading scenarios for heavy equipment with 3-D load paths and local attachments that affect stresses. Structural-stress methods are appealing for FE-driven twins and avoid the mesh-dependency of traditional methods. Notch or local approaches can more accurately represent the severity of the weld toe; however, they require local geometry, radius assumptions and mesh control [9,10]. Fracture mechanics is applicable after the crack has been detected or assumed and has some crack geometry and given a set of stress-intensity factors, stress history, and growth-law parameters [29–32]. These requirements are appropriate for a staged twin that is initiated in a stress domain (structural or notch stress) where uncertainty exists regarding the quality of the weld and then moves to a crack-state updating assessment when the weld is inspected or when SHM detects damage.

Table 4. Research gap and development matrix

Gap area	Current technical bottleneck	Consequence for lifecycle optimization	Needed development	Ref
Weld-process traceability	Manufacturing data are not consistently linked to FE entities	As-built variability is lost	Weld-specific digital thread and mesh registration	[14,15,18,39,40]
Residual-stress uncertainty	Measurement and simulation are incomplete	Crack-driving force uncertainty is underestimated	Probabilistic residual-stress fields and validation hierarchy	[8,12,34–36]
Sensor-to-crack interpretation	SHM features may not map directly to crack size	RUL cannot be updated reliably	Physics-informed feature inversion and probability-of-detection models	[24–28,29–32]
Local-global model coupling	Global FE misses local weld effects; local models are costly	Either excessive conservatism or missed hot spots	Adaptive sub modelling and surrogate correction	[9–11,19,20]
Operational load reconstruction	Duty cycles are nonstationary and asset-specific	Fatigue spectra may be inaccurate	Joint estimation of loads and structural state	[5,6,22,23,37]
Repair-state modelling	Repairs alter geometry, residual stress, and uncertainty	Maintenance may be falsely treated as a reset	Repair-aware FE and fatigue updating	[9,10,35–38,41]
Validation datasets	Field data are fragmented and proprietary	Model comparison remains weak	Shared benchmark datasets for welded assemblies	[3,4,17,25,38]
Decision metrics	Digital twins are often evaluated by prediction only	Economic and risk value is unclear	Metrics for inspection value, decision regret, and uncertainty calibration	[37,38]

There is no consensus in the literature as to which fatigue model is best for welded heavy equipment. The suitability is determined by the lifecycle stage and the available data. Structural-stress or notch approaches may be useful for design screening to give consistent ranking of weld critical locations. Measured strain histories can be mapped onto FE derived stress concentration relationships, for service monitoring. Fracture mechanics can be used to predict crack growth for post-detection prognosis, based on either measured dimensions or those from an inspection or SHM. In the case of multiaxial loading, critical plane and multiaxial weld fatigue should be taken into account, but computational cost and computational cost and parameter uncertainty increase [33]. This model-selection logic and the points at which each of the methods contributes to a "twin enabled workflow" are summarized in Table 3.

Another limiting factor is what is known as operational loading. Heavy equipment duty cycles are challenging to simulate in the lab using spectra. Nonstationary load histories are caused by payload, terrain, operator control, hydraulic pressures, impact and attachment configuration. The placement and calibration of strain gauges, hydraulic-pressure sensors, inertial measurement units, and controller-area-network signals can improve operational-load reconstruction. However, these measurements generally do not provide local weld stresses directly; local weld stresses must be inferred through calibrated global and local FE models. Digital twins should, therefore, be able to estimate load histories concurrently with the structural state, instead of assuming loads are known deterministic inputs.

This is confirmed by the evidence coded heatmap shown in Figure 2. Initialization and calibration are closely related to welding process logs, and are also closely related to diagnosis, if kept in a searchable digital thread. Stress and strain fields span widely between the calibration, prognosis and decision functions in FE. Inspection data for crack size are valuable for prediction as they can be used to parameterize fracture-mechanics models; however, inspection can be intermittent and may be affected by probability of detection. Vibration and guided-wave data can be used for diagnosis, requiring physics-based interpretation for prognosis. The distribution means that the lifecycle optimization should be designed as evidence fusion, instead of sensor substitution.

Optimization is the least developed layer for welded heavy equipment. The condition-based-maintenance literature provides a general framework for prognostics and decision-making [37,38] but welded structural assemblies create uncertainty based on repair and have non-trivial consequence models. A repaired weld does not regenerate or restore to its original condition. Future fatigue behaviour can be changed by gouging, grinding, rewelding, redistribution of residual stresses, local hardness changes, distortion, and inspection uncertainty. The lifecycle twin should treat each repair as a new manufacturing and structural-state event, with a new process record and a new FE state. This is true for reinforcement plates, weld toe grinding, peening, stress relieving operations and parts replacement. Optimization of maintenance should thus include not only the predicted RUL, but also inspection value, downtime cost, repair quality, residual risk, and future monitoring confidence.

The coded review corpus is then used to compare barriers to implementation by the different stages of the lifecycle in Figure 3. The highest number of barriers appears to be at cross-domain interfaces, not inside of the methods themselves. Variability is well known in welding FE, cost and calibration demands are well known in SHM, and parameter uncertainty is well known in fatigue prognosis. The more difficult task is to transfer information between them. For instance, weld bead scans and inspection records must be recorded in the FE mesh, sensor coordinates must be tracked after repairs, crack-state estimates must be recorded in a way compatible with fracture models, and maintenance actions must be accompanied by a change in geometry, material condition and uncertainty. These issues are just as much about digital-thread discipline as they are about algorithms.

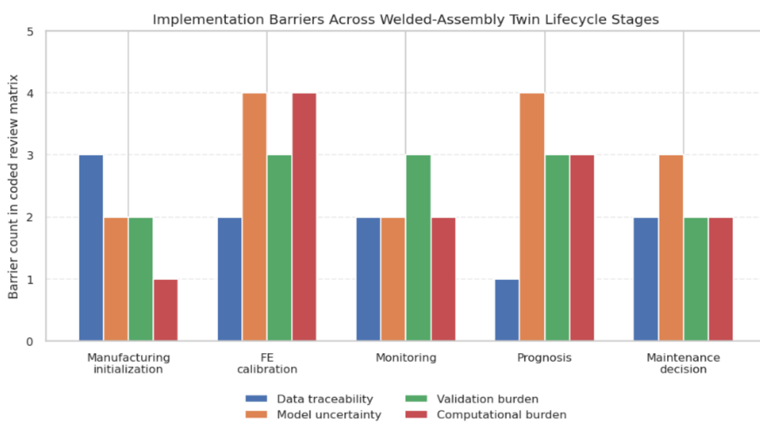

Figure 3. Implementation barrier counts by lifecycle stage

In Figure 4, the proposed integration graph suggested by the literature is shown. The thickest links are between FE models and fatigue prognosis and monitoring, as this topic is the subject of much mechanics and SHM research. Weaker links between manufacturing records and operational decision support verify a critical research gap. It is important as a weak point because optimization of the lifecycle relies on as-built variation. Because of distortion, bead shape or repair, or the presence of residual stress, two welded arms that appear to be identical might have different locations of fatigue critical sections. If there is no awareness of manufacturing, monitoring thresholds and maintenance schedules could be generalized incorrectly for those assets.

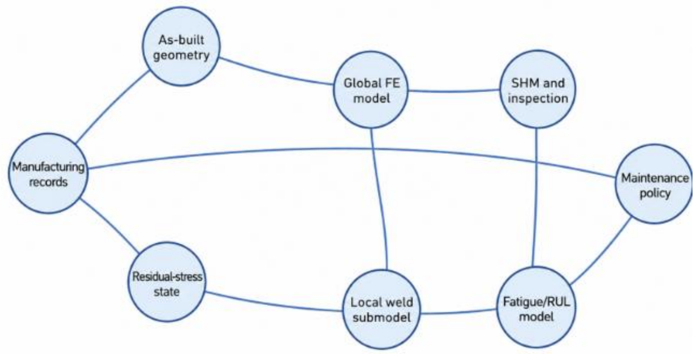

Figure 4. Weighted integration graph for welded-assembly digital twin SHM

The literature reviewed also indicates that the fidelity of the digital twin needs to be adaptive. It is often not feasible to use a full assembly-scale nonlinear transient welding-to-service twin for a fleet. However, local weld effects may not be captured in low fidelity twins. One defensible approach is to preserve a hierarchy: a global FE model is used to deal with load paths and boundary conditions; submodels are used for critical welds where structural or notch stress is of concern; fracture-mechanics models are used for found or assumed cracks; and surrogate models speed up repeated uncertainty propagation. For a limited set of welds, a selected weld detail class can be calibrated using high fidelity welding simulations or residual stress measurements. This hierarchy balances model fidelity, structural risk, and computational cost.

The major unresolved issue is validation. There are many papers on digital twin architectures, and many of the SHM papers have validated damage detection in controlled environments, but there is a need for validation of welded heavy equipment in realistic duty cycles, manufacturing scatter, environmental exposure, and repair. While laboratory specimens are still needed to isolate the mechanism, field validation is still needed for the credibility of the decision. The benchmark datasets should contain weld process histories, geometry scans, residual stress measurements, if possible, FE meshes, sensor streams, inspection records, crack-growth observation, maintenance actions, and loading histories. If these datasets are not available, optimizing a product's lifecycle will be hard to confirm.

The key technical implication is that digital twin–based SHM should be considered as an uncertainty-managed structural integrity framework, not as a real-time visualization platform. Data initializes the twin, FE models convert loads and geometry to stress and crack driving forces, SHM and inspection update the state, and prognostic decision models evaluate actions. While each element has well-developed and extensive literature, the entire chain is only as strong as the weakest data transformation. The current weakest transformations are for welded heavy equipment assemblies: (1) converting the manufacturing variability of the welds to a probabilistic structural state; (2) converting the sensor features to mechanically meaningful damage variables; and (3) converting the repair actions to a new model of the equipment's lifecycle. These gaps outline the research agenda.

5. Future Directions

Development of weld-aware digital thread should be a focus of future research. Manufacturing records should be recorded in a way which is directly related to the structural analysis, such as weld location, pass sequence, heat input proxies, filler material, operator/fixture identifier, fixture condition, preheat, temperature, inspection results, repair records, deviations from geometry and local deviations. This is not only a storage problem; it is also a semantic-alignment problem. Manufacturing records should be semantically linked to FE entities, weld-detail identifiers, sensor coordinates, and inspection zones. The workflows (or Lifecycle Logic) are housed in digital twin architecture studies [14,15,18,40] but more work is required for data schemas and mesh-registration methods for welds.

Probabilistic as-built modelling is a second priority. Only a limited subset of production welds can be represented using full-fidelity welding simulation or residual-stress measurement. Therefore, the probabilistic prior should be set up for weld geometry, residual stress, distortion, and defect states for the process class, inspection quality, past measurements, and selected high fidelity simulations. It is well founded mathematically in the Bayesian calibration [13] and for large welded assemblies, efficient computational methods are needed. Reduced-order models, surrogate models, local sub modelling and adaptive sampling should not be compared only with regard to computational speed, but with high fidelity welding FE and experimental residual stress measurements.

Third, SHM evidence must be linked more directly to structural mechanics. The data obtained from vibration, guided-wave, AE, strain and inspection data should be converted to state variables for the updating of the FE models or the fracture-mechanics models. These include modelling the sensor path, probability of detection (POD) characterization, compensation through the environment and mapping of features to crack states. There are several methods available in the existing SHM literature for operational-variability correction [24,25] and the foundations for local sensing exist with the guided wave and piezoelectric references [26,27]. The next step is to verify mechanically at weld details under realistic loading conditions applied by heavy equipment.

Fourth, the lifecycle optimization should be done with a view to maintenance and repair as state change events. All repair weld operations, grinding, peening, reinforcement, replacement of components and derating operations have an impact on geometry, confidence in inspection, residual stress and fatigue. After each intervention, parameters and uncertainties in the model should be adjusted in order to make the digital twin more realistic. The following requirements need to be fulfilled: current feedback from the field, decision algorithms that take into account the RUL, downtime, repair quality, and risk, and repair models that have been validated experimentally. The general framework is provided by condition based maintenance and RUL literature [37,38] but there is also the need for extensions to the general framework which are pertinent to the specific domain of welded structure repair.

Fifth, benchmark databases should be developed. A scientifically useful data set would contain information about the welding manufacturing data, geometry data, residual-stress measurements (for some of these measurements), FE meshes, operational loads, sensor streams, inspection history, crack growth observations and repair actions. Failure data and negative data should be incorporated in such datasets, since failure cases, non-failure cases, and false alarms are essential for evaluating maintenance decisions. Several weld classes, thicknesses, materials, loading modes and environmental exposures should be included in the data. Comparisons between the models will remain ad hoc until there are common datasets, where the models operate in different geometries and sensor configurations.

Last but not least, there must be established standard assessment criteria for welded-assembly twins. The accuracy of prediction of crack size is insufficient. Metrics that should be included are stress-field error, model-update stability, probability calibration, detection delay, false alarm rate, RUL uncertainty width, inspection value, computational latency, and maintenance decision regret. These metrics would motivate the use of digital twins for evaluating the quality of the lifecycle decisions, instead of complexity of the dashboard. The proposed research directions are the hybrid probabilistic twin that combines manufacturing information, FE mechanics, SHM evidence and maintenance economics via explicit uncertainty propagation.

6. Conclusion

The digital twin approach to the SHM of welded heavy equipment assemblies is scientifically interesting because the structural-integrity problem it addresses is not adequately addressed by individual design analysis, periodic inspection, or sensor monitoring. The assembly conditions for a welded assembly present variability in manufacturing, fatigue critical details, variable residual stresses, variable loading during operating life and variable repair history, all of which have an important influence on the lifecycle performance. A review of the literature shows that the technical components available are welding FE; residual-stress assessment; finite element model updating; SHM feature extraction; welded-joint fatigue assessment; fracture-mechanics prognosis; and condition-based maintenance. The unresolved challenge is their disciplined integration.

State continuity is the key to optimising the lifecycle. The as-built structural state should be initialized from the manufacturing records; loads and geometry should be translated to a local stress state and crack driving force by FE model; damage state should be fed into the as built structural state of the FE model by the SHM and inspection; and maintenance decision fed back to the FE model as a new manufacturing and structural event. If one of the interfaces fails, then the twin becomes a partial twin and has limited decision value.

Progress in the future will be based not only on the generic digital twin architecture, but also on the weld-specific implementation of the digital twin. This will include probabilistic residual stress fields, defect informed mesh updating, mechanically interpretable sensor features, prognosis for repair, and validated datasets from realistic service conditions. For heavy equipment, the most valuable digital twin will not necessarily be the most detailed, but the one whose uncertainties are quantified, reduced, and traceable, and can be updated throughout the assets' lifecycle.

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