EXPERIMENTAL TEST FACILITY DATA SYNTHESIS WITH THE DYNAMICAL SYSTEM SCALING METHODOLOGY

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Abstract

The Dynamical System Scaling (DSS) methodology is an innovative new scaling approach that, as the name implies, incorporates the system's dynamic response into the scaling framework. Through differential geometry and geodesics, the DSS presents a unified concept for viewing the evolution of a system's response during a transient. The system state is defined by the value of the quantity of interest and the rate of change of that quantity. The response is plotted as a trajectory on a phase diagram where the system moves from the initial state to the final state. Along the trajectory, each state point also has an associated process time value, which captures how far into the transient that particular state corresponds to. The phase diagram therefore provides much more information to the engineer than simply viewing the quantity of interest through time.

Following the DSS methodology, scaled versions of the phase diagrams may be determined for a particular transient of interest. These scaled phase diagrams enable synthesizing data from multiple test facilities at various scales together onto a single plot. This idea is similar to how the Fractional Scaling Analysis (FSA) allows for large and small break LOFT and SEMISCALE test data to "collapse" down to nearly identical curves, as presented by Wulff et al. (2009). The DSS methodology takes this concept one step further than FSA, however by computing the scale distortion as the geodesic separation between the different facility response trajectories. The scale distortion is therefore not only immediately "viewable" from the phase diagrams, but also quantifiable.

This paper determines the DSS response trajectories for the large break LOFT and SEMISCALE test data. The geodesic phase diagrams are presented along with the DSS scale distortion measure.

This paper is one among a series that will compare and contrast the DSS methodology with the H2TS and FSA methods for a variety of practical engineering applications.

Keywords: Scaling analysis, Dynamical systems, Time-dependent scale distortion, H2TS, FSA

1. INTRODUCTION

The Dynamical System Scaling (DSS) methodology is a powerful new approach to scaling that as the name implies incorporates the system's dynamic response into the scaling framework [1]. Several other papers within in this Topical Meeting present the DSS formalism [1]. Reference [2] relates DSS to the H2TS and FSA methodologies and Reference [3] develops a technique for applying DSS as a tool in optimizing the design of a test facility.

The 2005 and 2009 papers by Wulff et. al [4] showed how the Fractional Scaling Analysis (FSA) could be applied at a system level to provide a synthesis of data obtained from widely different scaled integral effect test facilities. Their analysis included different tests from the LOFT and Semiscale test programs, which simulated a Pressurized Water Reactor (PWR) response during a Loss-of-Coolant-Accident (LOCA) event. The Loss-of-Fluid-Test (LOFT) test facility design is based on 1/48 volume scaling of a 3000 MWt Westinghouse PWR, whereas Semiscale represents 1/1700 volume of the same PWR.

One of the main conclusions from the FSA analysis presented in [4] was that the data synthesis by FSA serves to exhibit facility-related differences of process patterns or scale distortion in a component. Regardless of the test facility size as well as the break area, the data appeared to collapse together through the FSA methodology.

A similar analysis is conducted here with the DSS methodology, focusing on the LOFT and Semiscale LBLOCA tests. Evaluating the experimental data from other break sizes is the subject of future work. Theoretical background for the analysis in this paper can be found in [1], [2] and [3].

2. DATA SYNTHESIS PERFORMED WITH THE FRACTIONAL SCALING ANALYSIS METHODOLOGY

Reference [4] presents the results from the data synthesis performed with the FSA methodology. The key results are summarized in Figures 2 through 8 of [4] where the normalized fractional pressure is plotted versus the Fractional Change Metrics for different test facilities and break sizes.

As stated in [4], data synthesis can be used to analyse facility-related differences of process patterns or scale distortions. More specifically the claim is that FSA serves to quantify the effect of scale distortion.

One of the conclusions was that for the selected Semiscale facility, the effect of break size was judged to be properly scaled. When the normalized fractional pressures for the Large and Small break are plotted relative to the Fractional Change Metric, the curves tend to collapse nearly into one later in the blowdown. This occurs despite the fact that the Small break blowdown time is 71 times longer than that for the Large break.

Wulff et al. (2009) also compared the LOFT and Semiscale LBLOCA test results [4]. They concluded that the two facilities exhibited similar blowdown dynamics despite the fact that LOFT is 37 times larger than Semiscale. The two blowdown times differ by only one-third. This similarity was expected considering that LOFT and Semiscale were scaled to preserve time for large-break LOCA.

For the SBLOCA blowdown, it was found that LOFT blowdown time is 4.7 times longer than that for Semiscale. More specifically, early on the transient with a high depressurization rate, the authors noted that LOFT appears to have its SBLOCA depressurization rate strongly reduced relative to Semiscale. The authors associated to distortions caused by the heat transfer from structures and possibly by greater fluid elasticity in the pressurizer, earlier system-wide flashing, or less cooling in steam generators, or more boiling in the core.

3. DATA SYNTHESIS PERFOMRED WITH THE DSS METHODOLOGY

3.1 Dimensionless Coordinates

Unless stated otherwise, all notation used throughout this paper is consistent with the notation in [1]. The DSS system level normalized integral balance equation is expressed as follows [1]:

$$\frac{d\beta}{dt} = \omega \tag{1}$$

In Eq. (1), β is the normalized conserved quantity of interest and ω is its time derivative, referred to as the normalized sum of the agents of change. Specifically for the depressurization transient, the normalized conserved quantity is the system pressure scaled by the initial pressure value:

$$\beta = P^{+} = \frac{P}{P_0} \tag{2}$$

The experimental data provides the time history of the conserved quantity (albeit at discrete points). The normalized sum of the agents of change is simply obtained by estimating its time derivative.

The process time is now defined as [1]:

$$\tau = \frac{\beta}{\omega} \tag{3}$$

As stated in [1], DSS defines the dimensionless reference (or clock) time by dividing the reference time by the action, τ_S. The action is defined as the integral of the temporal displacement rate, D, over the transient [1]:

$$\tau_S = \int_{t_I}^{t_F} (1 + D)dt \tag{4}$$

However as shown in Eq. 32 of [2] the action can be computed from the initial and final process times:

$$\tau_S = \tau_F - \tau_I \tag{5}$$

In DSS the action is chosen as the normalizing factor. This normalizing factor therefore accounts for not only the initial response values (which is typically all that are used for scaling analyses) but also the response values at the end of the transient. The remaining quantities are also normalized with respect to the action. Thus, the dimensionless coordinates are defined as:

$$\tilde{\Omega} = \omega\tau_S; \quad \tilde{\beta} = \beta; \quad \tilde{t} = \frac{t}{\tau_S}; \quad \tilde{\tau} = \frac{\tau}{\tau_S} \tag{6}$$

3.2 Similarity and Coordinate Transformations

As discussed in detail in [1], similarity within the DSS framework is governed by the normalized metric invariance (or process relativity principle) and the covariance principle. In a slight departure from the notation in [1], two facilities will be labelled in general facility 1 and facility 2 (compared to labelling the two facilities as prototype and model) and denoted by subscripts '*1*' and '*2*', respectively. The normalized metric invariance principle between facility 1 and 2 is:

$$d\tilde{\tau}_2 = d\tilde{\tau}_1 \tag{7}$$

The two facilities' coordinates are related via constant transformation parameters, λ_A and λ_B:

$$\beta_2 = \lambda_A\beta_1, \qquad \omega_2 = \lambda_B\omega_1 \tag{8}$$

As shown in [1], the normalized metric invariance and the covariance principle provide five sets of similarity criteria based on the specific choice of transformation parameters. The most general is the 2-2 affine transformation similarity criteria [1]:

$$\tilde{\Omega}_R = \lambda_A, \quad \tau_{SR} = \tau_R = t_R = \frac{\lambda_A}{\lambda_B} \tag{9}$$

In Eq. (9), the subscript '*R*' denotes the ratio of the values between facility 2 and facility 1.

3.3 Data Synthesis with DSS

A complication to synthesising the data from two separate, already constructed, experimental facilities with DSS is that the transformation parameters, λ_A and λ_B, are unknown. If both facilities were designed within the DSS framework relative to a full-scale prototype facility the transformation parameters could be estimated from their respective scaling analyses. However, "legacy" experiments such as LOFT and Semiscale were designed with the classic power-to-volume method and therefore no such transformation parameters exist. From the power-to-volume scaling the two test facilities were designed to preserve time relative to the prototypical PWR they represent. However the time scaling between the two facilities should be considered unknown for the purpose of the DSS scaling.

At first it may seem that the transformation parameters can be easily estimated from the data. Equation (8) shows that the ratio of the normalized responses provide λ_A and the ratio of the normalized time derivatives give λ_B. However, the transformations between facilities only apply at reference time locations that satisfy the similarity criteria given in Eq. (9). If facility 2 is twice time accelerated relative to facility 1, the ratios in Eq. (8) must be evaluated at facility 2 reference time locations equal to half those for facility 1. The "scaled-up" facility 2 reference time locations that correspond to facility 1's reference time locations are $t_{2,1} = t_1/2$. The subscript '*2,1*' denotes the reference time locations in facility 2 that correspond to the reference time locations for facility 1. A further complication is that the final point of reference time considered in the scaling analysis matters for DSS. Not only must the final reference time location satisfy the time scaling, but the transient's final process time value must satisfy the process time ratio as well as the action ratio.

In order to satisfy the stated requirements, data synthesis within the DSS framework must be an iterative process. For a given facility 1 reference time interval, the 'optimal' facility 2 reference time interval must be identified. This interval is 'optimal' in the sense that the DSS time similarity criteria are satisfied, namely that the action ratio equals the reference time ratio which equals the process time ratio. The transformation parameters can then be estimated directly from responses using the computed time scaling. However, if an 'optimal' reference time interval cannot be identified the two facilities are not similar.

An alternative way to describe the goal of satisfying the time similarity criteria in Eq. (9) is that the dimensionless reference time and dimensionless process time ratios must be unity. Substitute the dimensionless coordinate definitions in Eq. (6) into Eq. (9) to yield:

$$\tau_R = \tau_{SR}\tilde{\tau}_R = \tau_{SR} \rightarrow \tilde{\tau}_R = 1 \tag{10}$$

$$t_R = \tau_{SR}\tilde{t}_R = \tau_{SR} \rightarrow \tilde{t}_R = 1 \tag{11}$$

This alternative viewpoint allows synthesizing the data within the DSS framework independent of the transformation parameters. If two responses plotted in the $(\tilde{\tau} - \tilde{t})$ space collapse together, then the processes are similar. The transformation parameters that allow the process curves, plotted in the $(\beta - \tilde{\Omega})$ plane, to collapse together can then be estimated.

The data synthesis process begins by numerically evaluating β and its time derivative, ω, from the data tape for each test facility. The process time is then computed using Eq. (3). The specific reference time interval for each test facility must then be selected. Facility 1 will be assumed to be the "larger" facility and so its reference time interval will be fixed. The reference time interval for facility 2 must be varied until the 'optimal' interval is identified. However it may be useful to choose an initial guess and compare the responses. Over each facilities' reference time interval, compute the action and then the dimensionless coordinates. The process curves and $(\tilde{\tau} - \tilde{t})$ curves can then be compared.

The iterative procedure to find the 'optimal' facility 2 reference time interval is completed in two stages. The first stage finds the reference time interval that preserves the dimensionless reference time ratio, Eq. (11). Multiple reference time intervals may satisfy Eq. (11), within the desired convergence tolerance. The identified reference time intervals are considered ‘local optima’ in the optimization algorithm. The next stage is to examine if any of those ‘local optima’ also satisfy Eq. (10) and thus preserve the dimensionless process time ratio. Equation (10) is essentially the non-differential statement of the normalized metric invariance principle. Therefore by performing this two stage constrained optimization, the ‘optimal’ reference time interval is that which satisfies the normalized metric invariance principle.

For real experimental facilities, there is no guarantee that a true ‘optimal’ reference time interval exists. In such a case, the facility 2 reference time interval that allows the normalized metric to be matched as close as possible may be identified. The fact that the normalized metric was in fact not invariant represents that there is distortion between the two facilities. DSS therefore does not simply find arbitrary transformation parameters that allow two responses to collapse together. The transformations can only exist if the two responses preserve metric invariance and are therefore similar.

4. DSS LOFT AND SEMISCALE DATA SYNTHESIS

4.1 Experimental Data

Data synthesis with DSS is demonstrated using LOFT and Semiscale LBLOCA tests. For the LOFT test, data pressure histories were taken for the LOFT Large-Break LOCA test L2-5 given in the report by [5]. The Semiscale test data came from the Large-Break LOCA test S-06-3 from [6] (p. 85, PU-13 curve in [6]).

The LOFT and Semiscale LBLOCA test data are shown in Figure 1. The LBLOCA data is plotted over a time interval consistent with [4]. Since LOFT is the “larger” facility, the ‘optimal’ reference time interval for the Semiscale LBLOCA test must be identified. The Semiscale reference time interval in [4] is used as the initial guess in the iterative procedure described previously.

To facilitate the processing of the data, the responses have been approximated via split-lines as shown in Figure 2. The time derivatives are therefore constant over each of the different split-line segments. The method used to approximate the time derivative can be further refined and it is an area of investigation for future work.

The pressures are normalized by the pressure value at the initiation of the LOCA event, and the normalized (approximate) responses are compared in Figure 3.

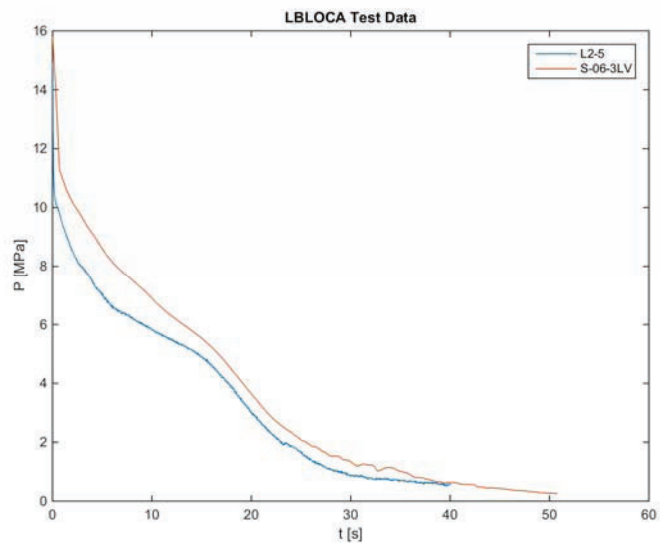

Figure 1 – LBLOCA Data (LOFT L2-5 and Semiscale S-06-3)

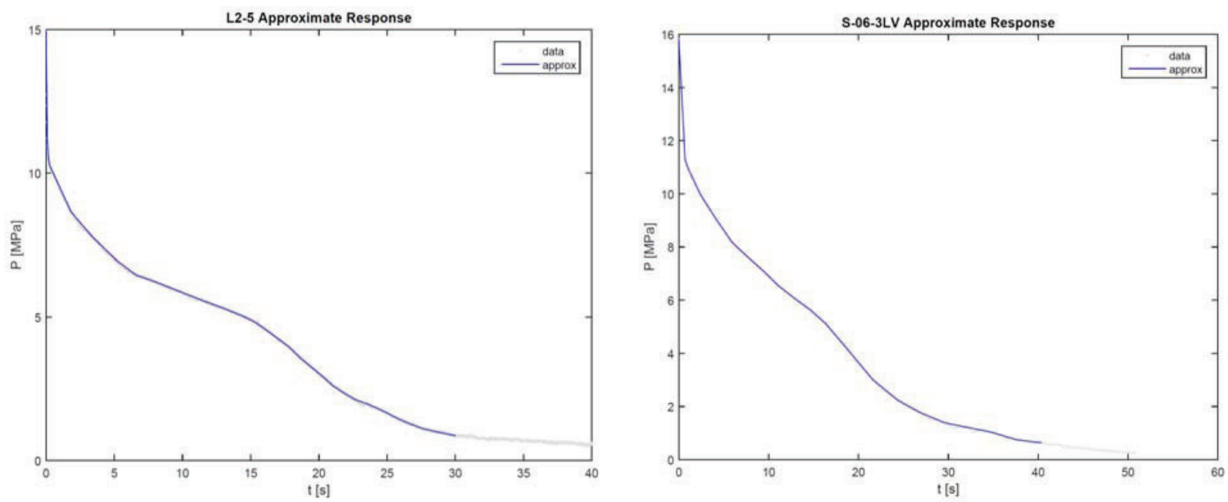

Figure 2 –Approximated Responses, LOFT (left) and Semiscale (right)

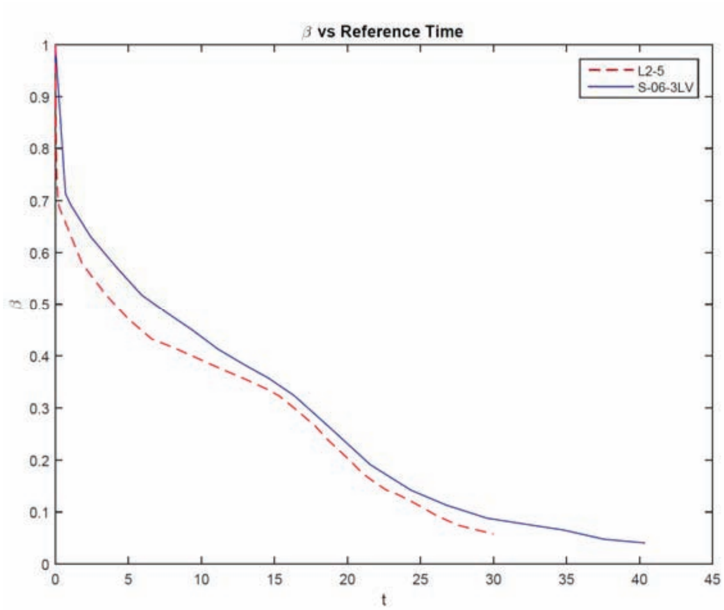

Figure 3 – Normalized responses vs reference time

4.2 LOFT and Semiscale Synthesis: Original Reference Time Interval

The first part of the iterative process is to compare the responses over the original or initial reference time interval guess for Semiscale LBLOCA test. The process times, actions, and dimensionless coordinates are computed for each facility as described previously. Before showing the process curves, the normalized responses are compared to the analogous plot from [4] in Figure 4. The Fractional Change Metric is the analogue to the DSS dimensionless reference time. As shown in Figure 4, the two plots share comparable traits, namely that the LOFT and Semiscale responses appear similar, especially over the rapid depressurization in the early part of the transient. There are several differences between the two sets of curves. It is unknown specifically how the LOFT and Semiscale data was processed in [4], therefore it is to be expected that some differences will exist. That being said, there is one major difference between the two sets of plots: DSS dimensionless reference time is negative. The FSA Fractional Change Metric is computed using the absolute value of the effective fractional rate of change. Thus the Fractional Change Metric is always positive.

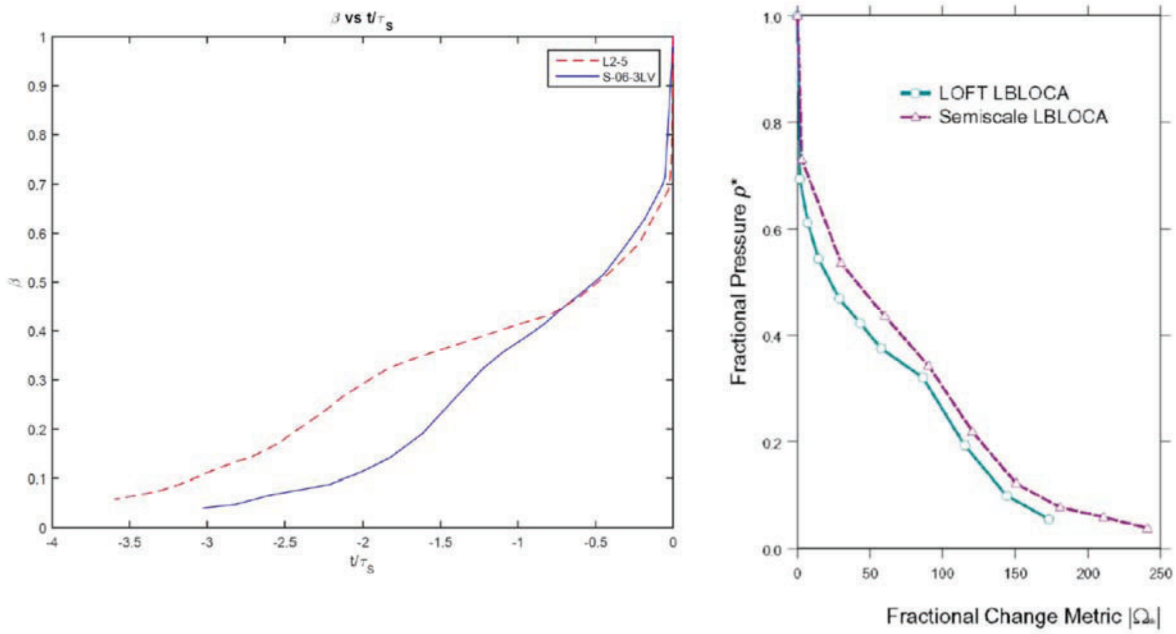

Figure 4 – DSS Normalized responses vs Dimensionless reference time compared to the analogous figure in Wulff et al. (2009) [4]

The dimensionless process curve trajectories are compared in the 3D $(\beta - \widetilde{\Omega} - \tilde{\tau})$ space in Figure 5. As explained in [1], the process curve completely captures the state of the system. The 3D process curve was not described in [1] but aids in the visualization of the present work. The process curve immediately makes apparent there are major differences between the LOFT and Semiscale results. Most notably, the early part of the transients appear to have the majority of the distortion, which is in sharp contrast to the conclusions drawn from Figure 4 and [4]. To aid in interpreting the results, 2D projections in the $(\beta - \widetilde{\Omega})$-plane (the 2D process curve described in [1]) and the $(\beta - \tilde{\tau})$-plane are shown in Figure 6. The 2D process curve makes it clear that there is significant distortion between the effect parameters during the initial part of the transient. Later on in the transient, when the trajectories appear to collapse together in the 2D process curve, the $(\beta - \tilde{\tau})$-plane reveals the trajectories diverge in the dimensionless process time coordinate.

The dimensionless coordinates shown in Figure 4 through Figure 6 do not consider the DSS transformation parameters. Note that chosen axis in Figure 4 is the dimensionless clock time $\tilde{t} = \frac{t}{\tau_S}$ whereas in Figure 5 the dimensionless process time is used instead, i.e. $\tilde{\tau} = \frac{\tau}{\tau_S}$.

None of the Semiscale dimensionless coordinates appear to be scalar multiples of the LOFT dimensionless coordinates. To confirm, the trajectories are plotted in the $(\tilde{\tau} - \tilde{t})$ space in Figure 7, which as described previously, is independent of the transformation parameters. The two trajectories clearly do not overlap which represents distortion is present over the original reference time interval considered for the Semiscale LBLOCA test.

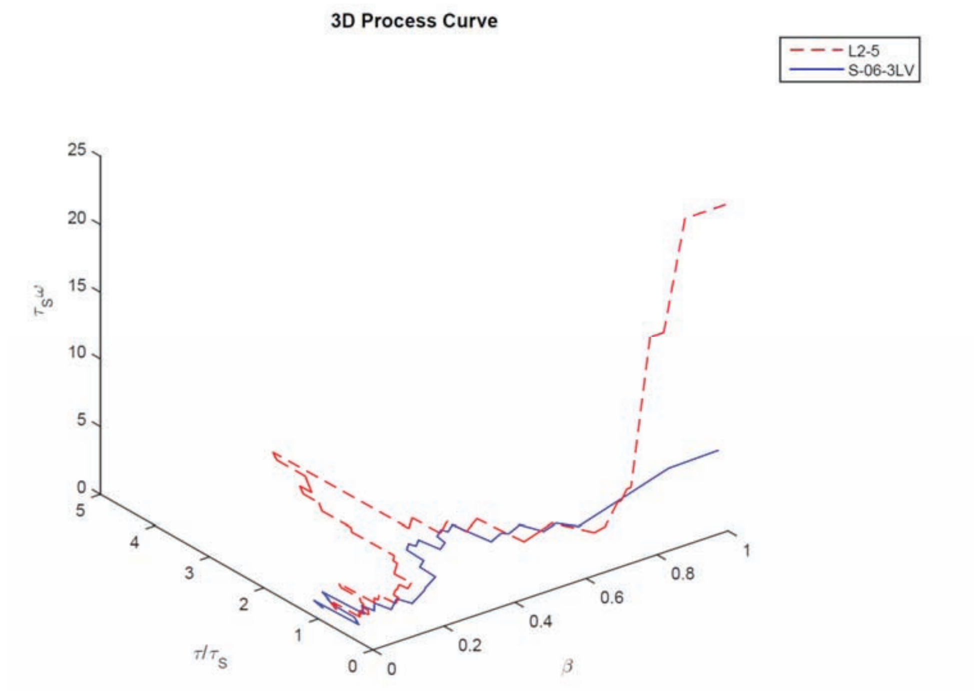

Figure 5 – 3D Process curve comparison between LOFT and Semiscale LBLOCA tests

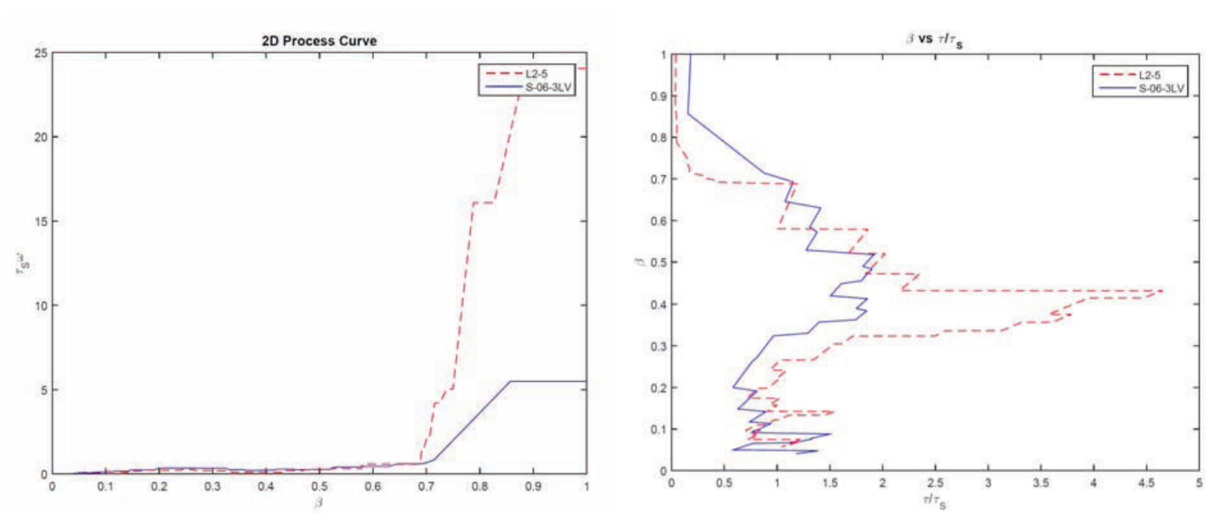

Figure 6 – 2D projections from the 3D process curve

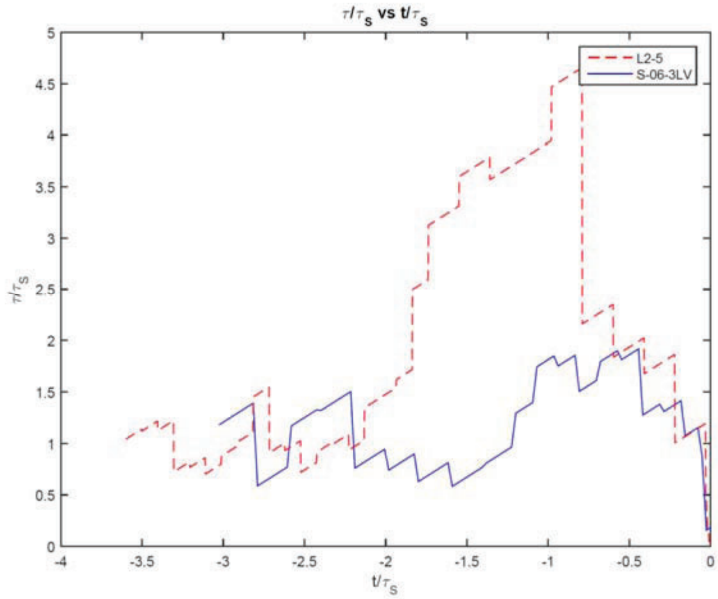

Figure 7 – Comparison of dimensionless process time vs dimensionless reference time trajectories

4.3 LOFT and Semiscale Synthesis: Find Optimal Reference Time Interval

Following the iterative process outlined in Section 3.3, the Semiscale reference time interval is now varied to try and identify the reference time interval that preserves both the dimensionless reference time and dimensionless process time ratios. The initial reference time location was fixed at 0 seconds, therefore the interval was defined by simply varying the final Semiscale reference time location. A final reference time location was ranged over 20 seconds to the original end time of 40 seconds. Four 'local optima' were identified that preserved the dimensionless reference time interval and those four locations are identified by circles in Figure 8. The four points are correspond to reference time values of roughly 21, 23, 29 and 35 seconds.

The next step is to compare the $(\tilde{\tau} - \tilde{t})$ trajectories to see if any of the 'local optima' preserve the dimensionless process time ratio. As shown in Figure 9, none of the four Semiscale curves exactly match the LOFT trajectory. However, one trajectory appears to be a closer match than the others, and that trajectory is highlighted in green. The corresponding optimum reference time interval was highlighted in Figure 8 by the green circle. The optimum trajectory was primarily selected on the basis that it appears to be the closest match to the LOFT trajectory in Figure 9.

The optimum trajectory captures the general trends in the LOFT trajectory, but it is clear that even though $\tilde{t}_R$ is preserved, $\tilde{\tau}_R$ is not preserved between the two responses. Therefore, even after identifying the optimum reference time interval distortion is still present between the LOFT and Semiscale LBLOCA tests.

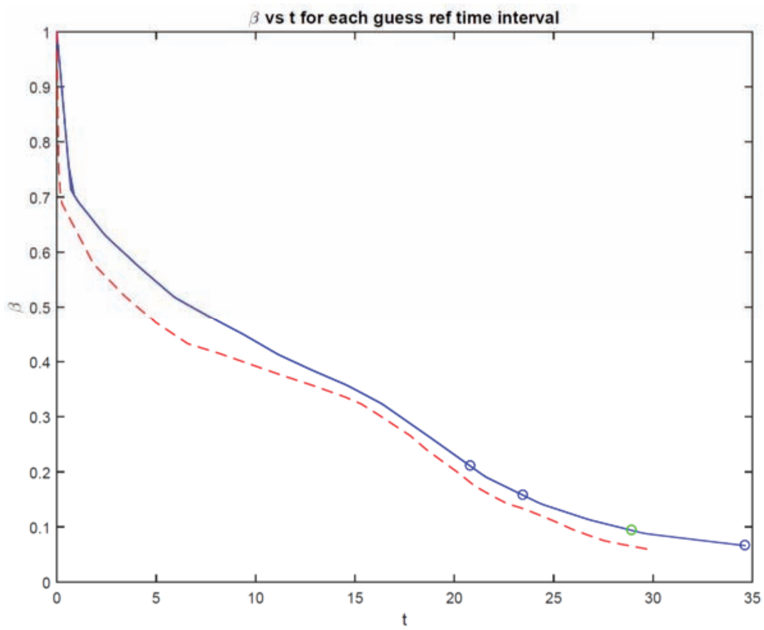

Figure 8 – Final reference time locations for the four identified 'local optima'

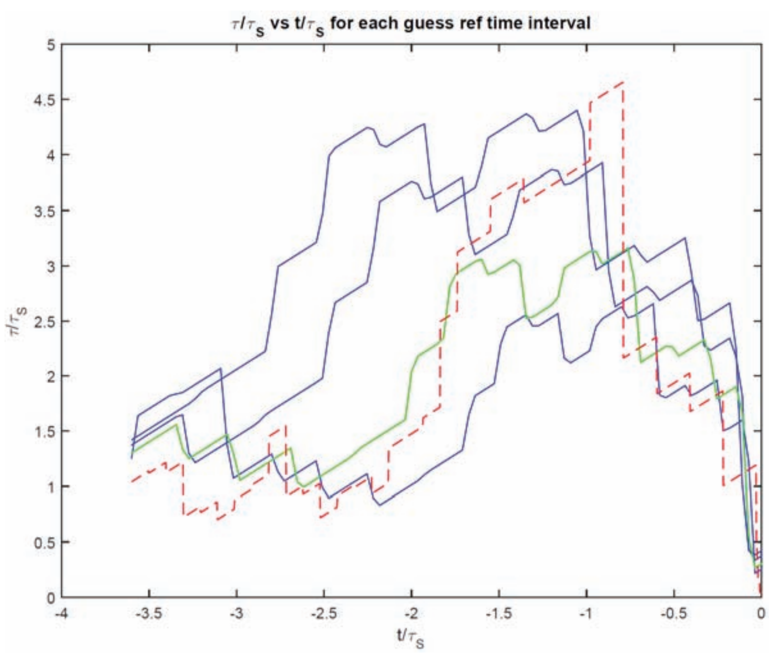

Figure 9 – Comparison of 'local optima' trajectories

4.4 LOFT and Semiscale Synthesis: 'Optimal' Comparisons

The same set of figures given for the original Semiscale reference time interval in Section 4.2 are now given for the 'optimal' reference time interval determined in the previous section. The optimal location corresponds to the Semiscale final reference time of roughly 29 seconds, which is nearly identical to the given LOFT final reference time location. The normalized responses as a function of the dimensionless reference time as computed over the optimal reference time interval are shown in Figure 10. Compared to the corresponding plot in Figure 4, the dimensionless reference time intervals are now the same between the two trajectories. Another difference between Figure 10 and Figure 4 is that now the LOFT and Semiscale trajectories do not overlap during the initial rapid depressurization. This more clearly illustrates that there is distortion between the facilities compared to the original Semiscale reference time interval.

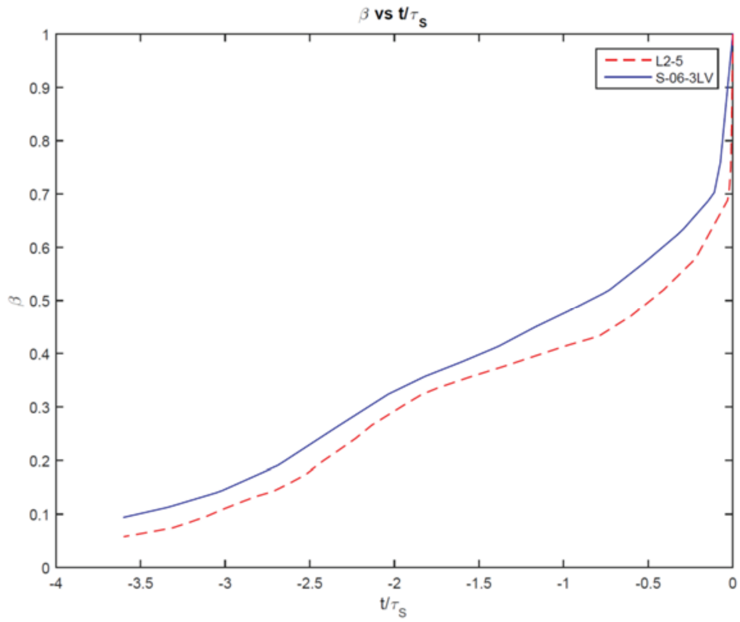

Figure 10 – Normalized responses vs Dimensionless reference time over the 'optimal' Semiscale reference time interval

The 3D process curves are compared in Figure 11. As expected there is a clear distortion between the two facilities that simply cannot be resolved, primarily in the early rapid depressurization phase. The 3D trajectories overlay better in the later stages of the transient in Figure 11 compared to Figure 5 which illustrates that distortion is truly a dynamic quantity that changes as the two processes evolve.

Arguably the early distortion that DSS method is able to highlight is associated with the significant heat metal heat releases in the Semiscale test during the blowdown. The metal heat release scales with the surface to liquid volume ratio which is significantly higher in Semiscale than in LOFT.

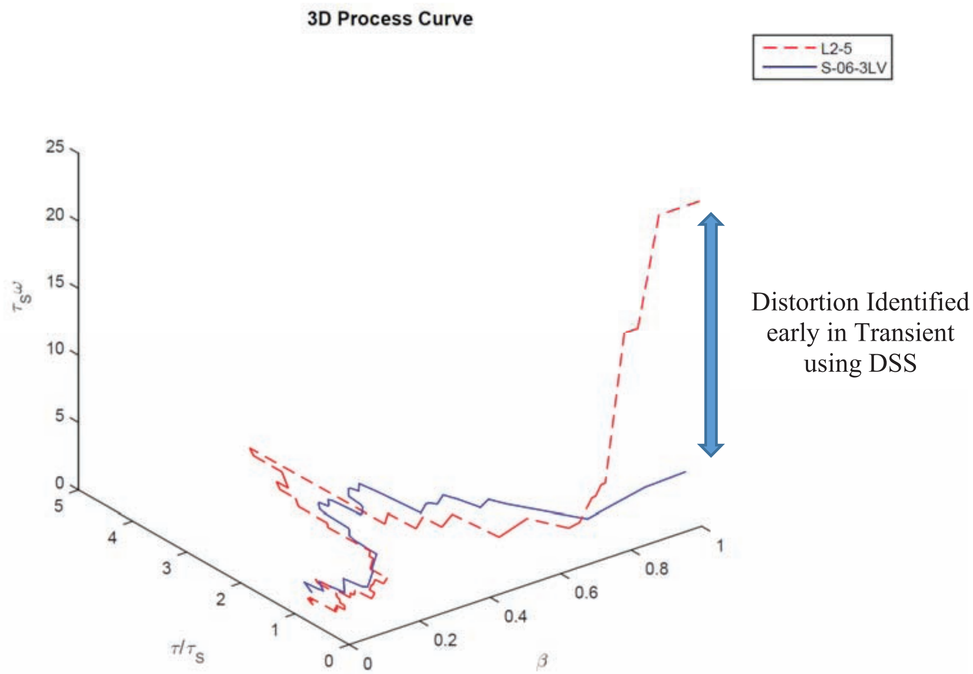

Figure 11 – 3D Process curve comparison over 'optimal' Semiscale reference time interval

5. CONCLUSIONS

This paper presented a few preliminary results on applying the Dynamical System Scaling (DSS) methodology to synthesize data from different test facilities. The idea that data synthesis is one of the purposes of the scaling analysis was introduced in the original work by Zuber on the Fractional Scaling Analysis in 2004 [7]. Wullf [4] showed FSA applied to the analysis of the LOCA depressurization from data obtained with LOFT and Semiscale test facilities.

Data synthesis can serve two purposes. First, it enables the analyst to down select the number of experiments that need to be simulated for code assessment. Second, it is a powerful tool to analyze facility-related differences of process patterns or scale distortions. More specifically the claim is that FSA serves to quantify the effect of scale distortion.

The Wulff analysis [4] was repeated here but the new DSS method was applied instead of FSA. The results presented in this paper are promising in the sense that DSS appears to quantify the distortions by considering the dynamic response of the system throughout the transient.

DSS requires that for an ideally scaled process, the corresponding geodesics will overlay exactly when plotted in normalized process space-time. However, any distortion in the scaling process will create a local separation between the two geodesics. If two tests were intended to represent the "LOCA" process, the separation between corresponding points on the test 1 and test 2 process curves, represents the scale distortion at a particular dimensionless process time $\tilde{\tau}$. The only scaling parameter considered in this analysis were the test facility size. Future work will also consider the impact of the break size.

It has to be acknowledged that the paper presents initial results from the application of DSS. More development is needed to fully benefit and optimize the implementation of the DSS methodology for the purpose of data synthesis. These research details will be presented in future work.

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