Model Reduction in Chemical Reaction Networks: A Data-Driven Sparse-Learning Approach

Omar A. Khalil\textsuperscript{a,*}, Farshad Harirchi\textsuperscript{a,*}, Doohyun Kim\textsuperscript{c}, Sijia Liu\textsuperscript{a}, Paolo Elvati\textsuperscript{c},
Angela Violi\textsuperscript{c,d}, Alfred O. Hero\textsuperscript{a,b}

\textsuperscript{a}Department of Electrical Engineering and Computer Science,
\textsuperscript{b}Department of Statistics,
\textsuperscript{c}Department of Mechanical Engineering,
\textsuperscript{d}Departments of Chemical Engineering, Biomedical Engineering,
Macromolecular Science and Engineering, Biophysics Program,
University of Michigan, Ann Arbor, MI 48109

\{oakhalil,harirchi,gogum,lsjxjtu,elvati,avioli,hero\}@umich.edu

December 27, 2017

Abstract

The reduction of large kinetic mechanisms is a crucial step for fluid dynamics simulations of combustion systems. In this paper, we introduce a novel approach for mechanism reduction that presents unique features. We propose an unbiased reaction-based method that exploits an optimization-based sparse-learning approach to identify the set of most influential reactions in a chemical reaction network. The problem is first formulated as a mixed-integer linear program, and then a relaxation method is leveraged to reduce its computational complexity. Not only this method calculates the minimal set of reactions subject to the user-specified error tolerance bounds, but it also incorporates a bound on the propagation of error over a time horizon caused by reducing the mechanism. The method is unbiased toward the optimization of any characteristic of the system, such as ignition delay, since it is assembled based on the identification of a reduced mechanism that fits the species concentrations and reaction rate generated by the full mechanisms. Qualitative and quantitative validations of the sparse encoding approach demonstrate that the reduced model captures important network structural properties.

1 Introduction

Combustion is a ubiquitous process with applications that vary widely from heating and transportation to mass production of metallic and ceramic nanoparticles. Despite its importance and several decades of intense scientific work, the chemical reaction networks that drive the processes are still elusive; they involve mechanisms that can span a wide range of length and time scales, highly reactive species, and are controlled by the delicate interplay between several chemical and physical phenomena. For all these reasons modeling has been extensively used to interpret and predict data on combustion. However, despite the massive increase in computational resources, we are still far from being able to simulate but the simplest systems once detailed fluid dynamic description is required. Specifically, using a detailed chemical description for the combustion of large molecules is still unrealistic, and instead reduced versions of the chemical kinetics have been developed.

Various reduction methods that exploit different mathematical model reduction algorithms have been proposed, including Principal Component Analysis (PCA) \cite{1}, Intrinsic Low Dimensional Manifolds \cite{2,3}, Computational Singular Perturbation (CSP) method \cite{4,5}, isomer lumping \cite{6}, and an optimization-based method \cite{7}. Also, the Directed Relation Graph (DRG) method and its derivatives \cite{8,9} have shown their

\*Similar contributions from these authors.

\^This research has been funded by the US Army Research Office grants W911NF-15-1-0241 and W911NF-14-1-0359.
capabilities to generate a skeletal version of very large detailed chemical mechanisms in a computationally ef-
ficient manner. However, since DRG-type approaches are species-based methods (they identify unimportant 
species and remove all reactions associated with them), they are not as effective as reaction-based methods 
for reducing chemical reaction networks. On the other hand, reaction-based mechanism reduction approaches 
(cls identify unimportant reactions and remove them) are able to calculate more compact reduced mech-

Optimization-based reaction elimination approaches also received some attention from the combustion 
community. For example, a nonlinear mixed-integer programming approach was proposed in [12, 13]. Because 
of the non-convex nature of these problems, they are computationally intractable, and their optimality is 
not guaranteed. In [7], an approach is proposed to obtain a group of reduced mechanisms that are only valid 
around one reference point (i.e., temperature, pressure, molar concentrations). This enables the approach to 
be formulated as a mixed-integer linear programming problem, which is achieved by linearizing the nonlinear 
ODE around a given reference point. This approach delivers a group of different reduced mechanisms that are 
valid locally around a reference point. Furthermore, it requires Jacobian evaluation that is computationally 
demanding.

In this paper, we propose a novel approach based on sparse-learning method to model reduction in 
chemical reaction networks. Our data-driven approach is part of the class of reaction-based methods, and 
hence carries the advantages associated with this class that are illustrated in figure 1. On the other hand, 
it does not require extensive number of simulations to capture sensitivity to different parameters. We pose 
the reaction-elimination problem as a mixed integer linear program, which can be solved to optimality in 

Our optimization-based approach identifies and removes unimportant reactions, by taking advantage of 
the relatively efficient manner, thanks to state-of-the-art MIP solvers [14]. As opposed to [7], the proposed 
approach aims to find a global reduced mechanism that is valid in the whole dynamical state space range. 
Our optimization-based approach identifies and removes unimportant reactions, by taking advantage of 
simulation data from the chemical process, and finds a global reduced mechanism with the minimal set of 
reactions, for which, the fitting error induced by removing the rest of the reactions remains in a user-specified 
bounded set. That is, the method finds the smallest set of reactions that still satisfy the bound condition 
on the error. Furthermore, it constraints the propagation of error caused by removing reactions in time. As 
the method is constructed based on finding a reduced mechanism that fits the species concentrations and 
reaction rates generated from the full mechanism, it is unbiased toward optimizing any specific characteristics 
such as ignition delay or temperature profile. In addition, the proposed method only requires tuning one 
parameter that has a physical meaning, which simply indicates the upper-bound on the tolerance of error 
caused by mechanism reduction. A preliminary version of this paper is presented in [15].

2 Modeling Framework

Chemical systems involve multiple species and reactions that describe how a set of chemical species interact 
through reactions and how their species concentrations evolve over time. The dynamics of chemical reactions 
are commonly modeled using mass-action kinetic equations [16, 17, 18, 19, 20]. Under Euler discretization 
method [21], the continuous dynamics can then be discretized as the following linear system

$$X_{t+1} = X_t + M r_t \Delta t + \omega_t, \quad t = 1, 2, \ldots, T - 1,$$

where $X_t$ is an $N_s \times 1$ vector of molar concentrations of all species at time $t$, $N_s$ is the number of species,
$N_r$ is the number of reactions, $M$ is an $N_s \times N_r$ matrix that contains the stoichiometric coefficients of all 
reactions, $\Delta t$ is the sampling time used for discretization, $\omega_t$ denotes the discretization error and process 
noise. $r_t$ is an $N_r \times 1$ vector of the reaction rates of all reactions at time $t$, which is a polynomial function 
of concentration values as follows:

$$r_t(i) = d_i \prod_{j=1}^{N_r} X_t(j)^{\alpha_{i,j}},$$

where $d_i$ is time varying reaction constant for the reaction $i$, $X_t(j)$ denotes the $j^{th}$ component of $X_t$, and 
$\alpha_{i,j}$ is the stoichiometric reaction coefficient relating reaction $i$ to species $j$. The values of $\alpha_{i,j}$ are contained 
in $M$. 

2
Figure 1: Schematic representation of a chemical reaction network and its reduction. The circular nodes are chemical species and the arrows are chemical reactions with the thickness representing their relative importance within the system. This illustration highlights that the reduction method proposed in this work can generate smaller reaction network compared to the one by typical species-based method by eliminating all less-influential reactions.

Given the discrete-time mass-action kinetic equations in Eq. (1), the focus of this paper is to infer a reduced mechanism, in terms of a reduced number of reactions, based only on observations such as species concentrations and reaction rates of the chemical systems.

3 Mechanism reduction via reaction selection

In this section, we propose a data-driven sparse-learning approach towards identifying a reduced set of reactions, which approximately replicates the behavior of the detailed mechanism.

For each of \( N_r \) reactions, we introduce a binary selection variable \( w_{i,t} \in \{0, 1\} \) to encode whether or not the \( i^{th} \) reaction is selected at time \( t \). If reaction \( i \) is chosen for the reduced mechanism at time \( t \), then \( w_{i,t} = 1 \); otherwise, \( w_{i,t} = 0 \). With the aid of the selection variables \( w_t = [w_{1,t}, w_{2,t}, \ldots, w_{N_r,t}]^T \), we formally state the problem of mechanism reduction.

**Problem Statement** Given the measurements of species concentrations \( X_t \) and reaction rates \( r_t \) at all times, determine the smallest subset of reactions (in terms of \( w \)) such that the estimation error induced by the reduced mechanism remains in a user-specified tolerance range (\( \epsilon \)) at all time instances.

3.1 Sparse-Learning Mechanism Reduction (SLMR)

Let us first define the error induced by the reduced mechanism characterized by \( w_t \) at time \( t \) on molar concentration of \( i^{th} \) species as follows:

\[
\mathcal{E}_{i,t}(w_t) = |X_{t+1}(i) - X_t(i) - M_i(w_t \odot r_t)\Delta t|, \tag{3}
\]

where \( M_i \) denotes the \( i^{th} \) row of matrix \( M \) and \( \odot \) denotes the element-wise product.

**Error tolerance on individual concentrations** We can enforce constraints on the error in the change of individual species concentrations for all time instances, i.e.,

\[
\mathcal{E}_{i,t}(w_t) \leq \epsilon N_t(i), \quad \forall t, \forall i \in \{1, \ldots, N_s\}, \tag{4}
\]

where \( N_t \) is the normalization factor at time \( t \), which is defined to be the summation of absolute changes of all concentrations at time \( t \) as described in Eq. (5), and \( \epsilon \) is a tuning parameter that indicates the error tolerance that is acceptable in terms of the percentage of \( N_t \), i.e., \( \epsilon = 0.05 \) indicates 5% error tolerance.
\[ N_i(t) = |M_i|r_t\Delta t, \ i \in \{1, \ldots, N_s\}. \] (5)

**Error propagation** Constraint Eq. (6) is added to avoid the propagation of error through time. The size of time horizon can be chosen based on the speed of changes in concentrations. We indicate such time horizon with \( H \). For the concentration change of each species \( i \) in time horizon \([t, t + H - 1]\), we have that

\[ |X_{t+H-1}(i) - X_t(i) - \sum_{k=t}^{t+H-2} M_i w_k \odot r_k \Delta k| \leq \beta \epsilon_{t+H-2} \sum_{k=t}^{t+H-2} N_k(i), \] (6)

where \( \beta \) is a tuning parameter that indicates the tightness of the bound on propagated error, and \( t = 0, H, 2H, \ldots \).

**Incremental reaction inclusion** At each time instance \( t \), we seek the minimum number of reactions that are required to be added to the previously selected reactions up to time \( t \) such that Eq. (4) and Eq. (6) are satisfied, i.e.,

\[ w_{t+1} \geq w_t. \] (7)

**Sparse-Learning Mechanism Reduction** Now that the constraints that we consider for the optimization problem are described, we can formulate our data-driven sparse-learning mechanism reduction approach. For each time batch of size \( H \), we solve the following mixed-integer linear programming problem:

\[
\{w^*_k\}_{k=t}^{t+H-1} = \begin{cases} \text{minimize} & \sum_{k=t}^{t+H-1} \sum_{i=1}^{N_r} w_{i,k} \\ \text{subject to} & w_{i,k} \in \{0, 1\}, \ i = 1, 2, \ldots, N_r, \\ & \forall k \in \{t, t+1, \ldots, t+H-1\} \\ & \text{Eqs. (4), (6), (7) hold.} \end{cases} \tag{P_{SLMR}}
\]

where \( \{w_k\}_{k=t}^{t+H-1} \) are the optimization variables. Note that solving problem (P_{SLMR}) delivers the minimum number of reactions that are required to be added to the previously selected reactions, \( i.e., \) incremental reaction inclusion Eq. (7) such that the error tolerance constraint on individual concentrations Eq. (4) and error propagation Eq. (6) are satisfied. The objective function minimizes the total number of selected reactions in the time horizon \([t, t + H - 1]\).

**Effect of different initial conditions** In order to have a global reduced mechanism that mimics the dynamical behavior of full mechanism, we need to use data from simulations over a sparse set of initial conditions that encompass the whole range of temperature \( T \), equivalence ratio \( \phi \) and pressure \( p \). We refer to each initial condition as a point in the parameter space, namely \( \theta = [T, \phi, p] \).

**Reduced mechanism for entire simulation time** The next step is to find the reduced mechanism not just for the time horizon \([t, t + H - 1]\), but for the entire simulation time \([0, t_f]\), where \( t_f \) is the time that simulation ends. In order to do this, we solve problem (P_{SLMR}) for time intervals \([0, H - 1], [H, 2H - 1], \ldots, [KH, t_f]\), where \( KH \) is the largest integer multiple of \( H \) that is smaller or equal to \( t_f \), as described in Algorithm 1.

**Global mechanism** Assume that data is available for a sparse set of initial conditions that is denoted by \( \Theta \). In order to obtain a global reduced mechanism we calculate the set union of all selected reactions for all the conditions in \( \Theta \). In other words:

\[ w^* = \bigcup_{\theta \in \Theta} R(w(\theta)), \] (8)

where \( R(w(\theta)) \) denotes the set of reactions corresponding to the output of Algorithm 1 for initial condition \( \theta \).
Algorithm 1 Calculating $w(\theta)$

Input: $\{X_t\}_{t=0}^{t_f}$, $\{r_t\}_{t=0}^{t_f}$, $\{\Delta_t\}_{t=1}^{t_f}$, $\epsilon$, $\beta$, $\theta = [\phi, T, p]$.

Initialize: $t = 0$, $w_{-1} = 0$.

1. While ($t \leq t_f$)
   - $W = \min\{H, t_f - t + 1\}$
   - set the time horizon to $[t, t + W - 1]$.
   - solve problem ($P_{SLMR}$) to obtain $w^*_tW-1$
     - $t + W \rightarrow t$.
   - $w_{t-1} = w^*_t$.

End while

2. Return $w^*_t$ as $w(\theta)$.

3.2 Computational Complexity

Problem ($P_{SLMR}$) is a standard mixed-integer linear programming (MILP) problem, and thus can be efficiently solved using state-of-the-art MILP solvers such as Gurobi [14] and CPLEX [22]. Even though these solvers can solve problems with large number of integer variables in a relatively fast manner by employing advanced branch and bounding algorithms, the worst-case complexity of MILP is exponential. In order to further reduce the complexity of our data-driven sparse-learning approach, we can utilize convex relaxation methods [23] by replacing the Boolean variable constraint with its convex compartment $0 \leq w_{i,t} \leq 1$ for all $i$. The latter yields a linear programming problem, which can be solved efficiently in polynomial time, and therefore makes our approach promising for extremely large-scale chemical reaction networks at the cost of losing optimality guarantees.

4 Application

We applied the reduction algorithm presented in the previous section to the chemical mechanism of H$_2$ oxidation by Hong et al. [24]. We selected this mechanism for two reasons: first is a very small mechanism that is suitable for testing of different approaches and as such optimal to develop new methodologies; second, due to the small number of reactions and species, is very difficult to reduce without affecting its accuracy. We want to stress, however, that the mechanism reduction of H$_2$ is intended to show the algorithm capabilities and not a real world application.

We first performed 48 simulations using the full mechanism in a H$_2$/air 0-D homogeneous reactor for thermodynamic regimes that relevant to practical combustion devices by using Chemkin [25]. The species concentrations and reaction rates generated for initial conditions encompassing 5 – 20 atm, 800 – 1100 K, and equivalence ratios between 0.5 – 2 were used to generate the reduced mechanism. We first fix the time horizon for error propagation to be at $H = 10$. Then, by setting the tuning parameters $\beta$ to 100 and $\epsilon$, i.e., the upper bound on the fitting error tolerance, to 0.02, 0.05, and 0.1 results in three reduced mechanisms with 47, 40 and 37 reactions (forward and reverse counted separately). Compared to the full mechanism, which includes 58 reactions excluding the reactions associated with Ar, that is a reduction of about 19%, 31%, and 36%, respectively.

Figure 2 shows, in the form of a directed bipartite graph, the comparison between the full mechanism and the 37-reactions reduced mechanism. In this representation, species are connected to the reactions in which they appear as reactants by red dashed lines, while reactions are connected to their products by blue dotted lines. Finally, gray lines show the reactions that were removed by the mechanism reduction.

To test the quality of the reduced mechanisms, we compared calculated ignition characteristics and the time evolutions of species concentrations in a range of conditions slightly wider than the one used to generate them (i.e., 5 – 20 atm, 700 – 1300 K, equivalence ratio of 0.5 – 2) for the same homogeneous
Such as ignition characteristics and heat release, as well as species profiles during pre-ignition and ignition.

Overall, however, the above comparisons show that the reduced mechanisms generated by our new reduction approach are effective in reproducing key combustion properties reached in the concentrations after ignition. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism. However, OH profiles show that the correct ignition event compared to those from the full mechanism.

The relative deviation in the ignition delay times are, however, even in the worst case scenario within 1% under all the tested conditions. Also the maximum temperature increase (bottom panels of Fig. 3) is well-maintained in the reduced mechanisms. This agreements are not limited to 10 atm and $\phi = 0.5$ and 1, as very similar observations can be made in all the condition tested (not shown).

Figure 4 shows the time evolutions of selected species for the simulations at 1000 K, 10 atm, equivalence ratios of 0.5 and 1. All three reduced mechanisms are in excellent agreement with the full mechanism, with, as expected, larger reduced mechanisms showing better agreements. The relative deviation in the ignition delay times are, however, even in the worst case scenario within 1% under all the tested conditions. Also the maximum temperature increase (bottom panels of Fig. 3) is well-maintained in the reduced mechanisms. This agreements are not limited to 10 atm and $\phi = 0.5$ and 1, as very similar observations can be made in all the condition tested (not shown).

Figure 2: The directed bipartite graph for the reduced mechanism with 37 reactions ($\epsilon = 0.1$). Red dashed lines indicate the edges from species to reactions, blue dotted lines represent the edges from reactions to species, and light grey solid lines show the removed edges from the detailed mechanism.

reactor. Figure 3 shows the ignition delay times, relative deviations in ignition delay time from the full mechanism, and maximum temperature increase at 10 atm, and equivalence ratios of 0.5 and 1. All three reduced mechanisms are in excellent agreement with the full mechanism, with, as expected, larger reduced mechanisms showing better agreements. The relative deviation in the ignition delay times are, however, even in the worst case scenario within 1% under all the tested conditions. Also the maximum temperature increase (bottom panels of Fig. 3) is well-maintained in the reduced mechanisms. This agreements are not limited to 10 atm and $\phi = 0.5$ and 1, as very similar observations can be made in all the condition tested (not shown).
Figure 3: Computed ignition delay times (top), percent deviations in ignition delay from the full mechanism (middle), and maximum temperature increase (bottom) for 10 atm, equivalence ratios of 0.5 and 1 cases.

Figure 4: Time evolutions of H₂O, H, and OH in mole fractions from homogeneous reactor simulations with initial conditions of 1000 K, 10 atm, and equivalence ratios of 0.5 and 1.

5 Conclusions

In this work, we present a new method to reduce chemical reaction network by employing data-driven sparse learning approach to obtain a reduced mechanism that is valid for all process conditions (temperature, pressure and equivalence ration) and all ranges of species molar concentrations. In addition, our method incorporates a user-specified bound on the propagation of error cause by eliminating reactions. That is, the proposed approach ensures that the discrepancy between the original and the reduced mechanisms remains in the user-specified acceptable range in all time instances and in all time horizons of specified length. The reduction is performed without introducing any bias towards specific properties or species therefore providing a mechanism with optimal performance, which is independent of the chemical reaction network that is being considered. Finally, the approach has a low computational cost and scales gracefully with the size of the full mechanism, making it a viable option for the reduction of large mechanisms.

The performance of the method is evaluated on a H₂ mechanism, which due to its small initial size was expected to be difficult to reduce. Surprisingly, however, our method was able to reduced the number of
reactions by more than one third without any notable discrepancy in ignition delay or heat release.

References

[1] S. Vajda, P. Valko, and T. Turányi. Principal component analysis of kinetic models. *International Journal of Chemical Kinetics*, 17(1):55–81, 1985.

[2] U. Maas and S. B. Pope. Implementation of simplified chemical kinetics based on intrinsic low-dimensional manifolds. *Symposium (International) on Combustion*, 24(1):103–112, 1992.

[3] U. Maas and S. B. Pope. Simplifying chemical kinetics: Intrinsic low-dimensional manifolds in composition space. *Combustion and Flame*, 88(3):239–264, 1992.

[4] S. H. Lam and D. A. Goussis. The CSP method for simplifying kinetics. *International Journal of Chemical Kinetics*, 26(4):461–486, 1994.

[5] S. H. Lam. Using CSP to Understand Complex Chemical Kinetics. *Combustion Science and Technology*, 89(5-6):375–404, 1993.

[6] Syed Sayeed Ahmed, Fabian Mauss, Gladys Moréac, and Thomas Zeuch. A comprehensive and compact n-heptane oxidation model derived using chemical lumping. *Physical Chemistry Chemical Physics*, 9(9):1107–1126, 2007.

[7] Binita Bhattacharjee, Douglas A. Schwer, Paul I. Barton, and William H. Green. Optimally-reduced kinetic models: Reaction elimination in large-scale kinetic mechanisms. *Combustion and Flame*, 135(3):191–208, 2003.

[8] Tianfeng Lu and Chung K. Law. A directed relation graph method for mechanism reduction. *Proceedings of the Combustion Institute*, 30, 2005.

[9] P Peiotdesjardins and H Pitsch. An efficient error-propagation-based reduction method for large chemical kinetic mechanisms. *Combustion and Flame*, 154(1-2):67–81, 2008.

[10] T Lu and C Law. Strategies for mechanism reduction for large hydrocarbons: N-heptane. *Combustion and Flame*, 154(1-2):153–163, 2008.

[11] Kyle E. Niemeyer, Chih-Jen Sung, and Mandhapati P. Raju. Skeletal mechanism generation for surrogate fuels using directed relation graph with error propagation and sensitivity analysis. *Combustion and Flame*, 157(9):1760–1770, 2010.

[12] Linda Petzold and Wenjie Zhu. Model reduction for chemical kinetics: An optimization approach. *AIChE journal*, 45(4):869–886, 1999.

[13] Keith Edwards, TF Edgar, and VI Manousiouthakis. Reaction mechanism simplification using mixed-integer nonlinear programming. *Computers & Chemical Engineering*, 24(1):67–79, 2000.

[14] Inc. Gurobi Optimization. Gurobi optimizer reference manual, 2016.

[15] Farshad Harirchi, Omar A. Khalil, Sijia Liu, Paolo Elvati, Angela Violi, and Alfred O. Hero. A data-driven sparse-learning approach to model reduction in chemical reaction networks. In *Proceedings of NIPS 2017 Workshop on Advances in Modeling and Learning Interactions from Complex Data*, 2017.

[16] Martin Feinberg. Chemical reaction network structure and the stability of complex isothermal reactors—i. the deficiency zero and deficiency one theorems. *Chemical Engineering Science*, 42(10):2229–2268, 1987.

[17] Jeremy Gunawardena. Chemical reaction network theory for in-silico biologists. *Notes available for download at [http://vcp.med.harvard.edu/papers/crnt.pdf]*, 2003.

[18] Daniel T Gillespie. Stochastic simulation of chemical kinetics. *Annu. Rev. Phys. Chem.*, 58:35–55, 2007.
[19] Vijaysekhar Chellaboina, Sanjay P Bhat, Wassim M Haddad, and Dennis S Bernstein. Modeling and analysis of mass-action kinetics. *IEEE Control Systems*, 29(4):60–78, 2009.

[20] David F Anderson and Thomas G Kurtz. Continuous time markov chain models for chemical reaction networks. In *Design and analysis of biomolecular circuits*, pages 3–42. Springer, 2011.

[21] Uri M Ascher and Linda R Petzold. *Computer methods for ordinary differential equations and differential-algebraic equations*, volume 61. Siam, 1998.

[22] IBM ILOG CPLEX. User’s manual for CPLEX. *Int. Bus. Mach. Corp.*, 46(53):157, 2009.

[23] Jorge Nocedal and Stephen J. Wright. *Numerical Optimization*. Springer, New York, NY, USA, second edition, 2006.

[24] Zekai Hong, David F. Davidson, and Ronald K. Hanson. An improved H2/O2 mechanism based on recent shock tube/laser absorption measurements. *Combustion and Flame*, 158(4):633–644, 2011.

[25] CHEMKIN version 18.0, 2016.