

Stochastic Navier-Stokes equations: ideas and results using nonstandard analysis

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(Joint with Marek Capiński, Jerry Keisler, Kasia Grzesiak, Brendan Enright)

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Aim of the talk: to sketch informally the Loeb space approach and what can be achieved in these areas.

Mathematical Formulation - Hilbert space setting

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The sNSE are now formulated as a **stochastic differential equation** in \mathbf{H} :

$$du = [-\nu Au - B(u) + f(t, u)]dt + g(t, u)dw_t$$

Initially regard this as an equation in \mathbf{V}' (the dual of \mathbf{V}) although it turns out that solutions live in \mathbf{H} (and in fact in \mathbf{V} for almost all times).

$$du = [-\nu Au - B(u) + f(t, u)]dt + g(t, u)dw_t \quad (1)$$

The equation is understood as a **weak integral equation** :

$$u(t) = u_0 + \int_0^t [\nu Au(s) - B(u(s)) + f(s, u(s))]ds + \int_0^t g(s, u(s))dw_s$$

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Note The pressure has disappeared, because $\nabla p = 0$ in \mathbf{V}' .

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Loeb space methods provide a **single** space Ω (a Loeb space) and a Wiener process w carrying solutions for **all** (random) initial conditions and **all** f, g .

This makes them powerful for discussing attractors and optimal control theory for sNSE. Loeb spaces are *saturated* and *homogeneous*.

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An example of a non-zero infinitesimal is given by $(1, \frac{1}{2}, \frac{1}{3}, \dots)/\mathcal{U}$.

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$({}^*\mathbb{R}, +, \times, <)$ is an ordered field.

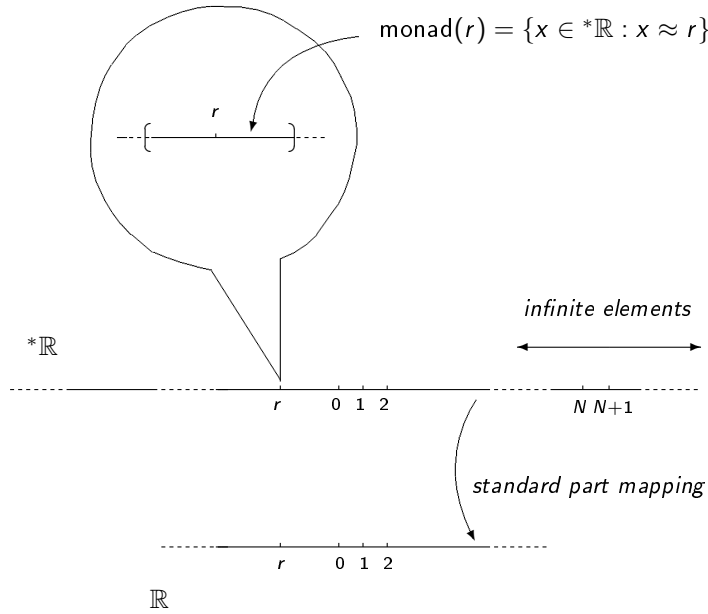
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A good way to picture ${}^*\mathbb{R}$ is as follows (note that some features in the diagram are yet to be explained).

Infinitesimal microscope

$$\text{monad}(r) = \{x \in {}^*\mathbb{R} : x \approx r\}$$



The Hyperreals

Now extend *all* sets A , functions f and relations R on \mathbb{R} to ${}^*\mathbb{R}$ pointwise – with the extensions denoted by *A , *f and *R .

Examples: ${}^*\mathbb{N}$, ${}^*\mathbb{Z}$ and ${}^*\mathbb{Q}$, the sets of *hypernatural numbers*, *hyperintegers* and *hyperrationals* respectively. We can talk about an infinite (hyper)natural number N .

Properties of ${}^*\mathbb{R}$ are given systematically by the following:

Theorem (Transfer Principle)

Let φ be any first order statement. Then

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A **first order statement** φ (respectively $^*\varphi$): refers to elements of \mathbb{R} (respectively $^*\mathbb{R}$), both fixed and variable, and to fixed relations and functions f, R (respectively $^*f, ^*R$), with quantification ($\forall x, \exists y$) only for *elements*.

Properties of ${}^*\mathbb{R}$ are given systematically by the following:

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Definition (Standard Part)

If x is a finite hyperreal the unique real $r \approx x$ is called the **standard part of x** , written $r = {}^\circ x = \text{st}(x)$.

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Repeat the above construction to give *A for any mathematical object or structure A ; e.g. *M for a metric space with $d : M \times M \rightarrow \mathbb{R}$.

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Remark The standard part mapping extends to the “nearstandard” elements of any extension metric (or topological) space *M - in particular the space ${}^*\mathbf{H}$. It is easy to show that elements U in ${}^*\mathbf{H}$ with $|U|$ finite are *nearstandard* in the *weak topology*.

LOEB MEASURES

A *Loeb measure space* is a measure constructed from a nonstandard (i.e. *internal*) measure (essentially it is an **ultraproduct of measures**).

Suppose that an internal set Ω and an internal algebra \mathcal{A} of subsets of Ω , are given, μ is a finite internal finitely additive measure on \mathcal{A} ;

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Theorem (Loeb 1975)

*There is a unique σ -additive extension of ${}^\circ\mu$ to the σ -algebra $\sigma(\mathcal{A})$ generated by \mathcal{A} . The completion of this measure is the **Loeb measure corresponding to μ** , denoted μ_L and the completion of $\sigma(\mathcal{A})$ is the *Loeb σ -algebra*, denoted by $L(\mathcal{A})$.*

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Similar relationships connect internal (i.e. nonstandard) stochastic integrals to standard stochastic integrals on the Loeb space.

LOEB SPACE SOLUTIONS TO STOCHASTIC NSe

(1) Use standard SDE methods + Transfer to solve the Galerkin approximation to the sNSe in dimension N ($N \in \mathbb{N}$ infinite)

$$dU(\tau) = [-\nu^*AU(\tau) + ^*B_N(U) + ^*f_N(\tau, U(\tau))]d\tau + ^*g_N(\tau, U(\tau))dW_\tau$$

U is an internal stochastic processes $U : [0, T] \times \Omega \rightarrow \mathbf{H}_N \subset \mathbf{H}$ on an internal space $\mathbf{\Omega}_0 = (\Omega, \mathcal{A}, \mathcal{P})$ with internal Wiener process W in \mathbf{H}_N

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(2) Establish an **energy estimate**. There is a **finite** constant E (independent of N) such that

$$\mathbb{E} \left(\sup_{\tau \leq T} \|U(\tau)\|^2 + \nu \int_0^T \|U(\sigma)\|^2 d\sigma \right) < E \quad (\text{Energy})$$

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(5) Show that this u solves the sNSe on the Loeb space corresponding to Ω_0 i.e. $\Omega = (\Omega, L(\mathcal{A}), \mathcal{P}_L)$ with filtration derived from that on Ω_0

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Theorem (Capiński & NJC (1991))

There is an adapted probability space Ω carrying an H -valued Wiener process w such that for any (L^2 -random) $u_0 \in H$ and f, g (continuous with linear growth) there is a (weak) solution of the stochastic Navier–Stokes equations.

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That is, an adapted stochastic process $u : [0, \infty) \times \Omega \rightarrow H$ such that for a.a. ω

(i) $u \in L^2(0, T; V) \cap L^\infty(0, T; H) \cap C(0, T; H_{\text{weak}})$ for all $T < \infty$,

(ii) for all $t \geq 0$

$$u(t) = u_0 + \int_0^t [\nu Au(s) - B(u(s)) + f(s, u(s))] ds + \int_0^t g(s, u(s)) dw_s$$

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Loeb space methods give new results for each of (2) - (4) for sNSE for drift and noise of the form $f(u)$ and $g(u)$

Stochastic attractors for sNSE

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Making this precise gives:

Theorem

(Capiński & NJC 1999) For special forms of the noise term $g(u)$ in the 2D sNSe there is a stochastic attractor $A(\omega)$ (compact in the strong topology of \mathbf{H}).

Precise definition and proof - too long and complicated!

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This has the crucial semi-flow property $S_{t_1} \circ S_{t_2} = S_{t_1+t_2}$ along with $S_0 u = u$.

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This has the crucial semi-flow property $S_{t_1} \circ S_{t_2} = S_{t_1+t_2}$ along with $S_0 u = u$.

Theorem (Sell (1996))

There is global attractor $A \subseteq \mathbf{W}$ for the 3-dimensional (deterministic) Navier–Stokes equations.

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This turns out to be asking too much. We need a weaker definition. In the following, if u is a stochastic process then $\text{Law}(u)$ is defined to be the probability law (on path space) of the coupled process (u, w) .

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Even for this weaker definition, existence requires a rather large probability space

Theorem

(NJC & H.J.Keisler,2004)There is a Loeb space Ω and a natural class of solutions X that has a process attractor A . The class X contains solutions to the sNSe for all L^2 random initial conditions.

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Remark It can be shown that if Ω is any sufficiently rich space (for example if Ω is a Loeb space) then any process attractor A is **not** compact.

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- (2) A is **neocompact**;
- (3) for any **neo-open** set $G \supset A$ and bounded set $B \subset X$, eventually $S_t B \subseteq G$.

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This idea has been applied to the sNSe in a variety of settings, always involving a Loeb space so that solutions for all controls live on the same probability space.

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Using NSA for optimal control problems

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$$\text{Cost of using control } \theta_n = J(\theta_n) \searrow J_0$$

where J_0 is the **infimum of all costs** for controls for the given system.

Then NSA allows us to speak of the **nonstandard control** θ_N for any infinite N . We can usually make sense of $J(\theta_N)$ and we will have $J(\theta_N) \approx J_0$. In many circumstances we can then “take standard parts” to produce an **optimal control**

$$\theta = \circ\theta_N$$

This idea has been applied to the sNSe in a variety of settings, always involving a Loeb space so that solutions for all controls live on the same probability space. Results have been obtained for **2D** systems of the form

$$u(t) = u_0 + \int_0^t \{-\nu Au(s) - B(u(s)) + f(s, u, \theta(s, u))\} ds + \int_0^t g(s, u) dw(s)$$

with θ Hölder continuous, or with θ having no feedback in u , or with the feedback consisting of cumulative digital observations of the solution at a fixed finite number of times.

For the **3D equations** results are only for systems with no feedback: i.e. $\theta = \theta(t)$. The possible non-uniqueness of solutions requires a large space to work in - one containing all possible solutions for a given control to allow initially the existence of an optimal solution for a given control.

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$$U(\tau) = U_0 + \int_0^\tau \{-\nu^* A U(s) - {}^* B(U(s)) + {}^* f(s, U, \Theta(U))\} ds \\ + \int_0^\tau {}^* g(s, U) dW(s)$$

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where $U : {}^*[0, T] \rightarrow {}^*\mathbf{H}$ or \mathbf{H}_N . Then we “standardise” the control to give $\theta = {}^\circ\Theta$ and as in the basic existence proof show that it is possible to take $u(t, \omega) = {}^\circ U(t, \omega)$. It remains to prove that u is a solution for control θ and $J(\theta) = {}^\circ J(\Theta)$ to give optimality.

Details: NJC & K.Grzesiak: Stochastics (2005) and AMO (2007).

Application 3: NON-HOMOGENEOUS (i.e. non-constant density) STOCHASTIC NSE with multiplicative noise

These model the **velocity** u and **density** ρ of a mixture of viscous incompressible fluids of varying density in a bounded domain $D \subset \mathbb{R}^d$ ($d = 2, 3$)

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(3) Loeb space methods (NJC & Brendan Enright): solve the *stochastic* equations with general *multiplicative* noise for $d = 2, 3$ assuming $M \geq \rho_0 \geq m > 0$.

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Note. $g = 0$ gives Kazhikhov's definition for the deterministic equations.

Theorem (NJC & Brendan Enright, JDE 2006) *Suppose that $u_0 \in H$ and $\rho_0 \in L^\infty(D)$ with $0 < m \leq \rho_0(x) \leq M$, and f, g satisfy natural continuity and growth conditions. Then there is a weak solution (ρ, u) to the stochastic nonhomogeneous Navier-Stokes equations with*

$$\mathbb{E} \left(\sup_{t \leq T} |u(t)|^2 + \nu \int_0^T \|u(t)\|^2 dt \right) < \infty$$

and for almost all ω , for all t

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$$\Omega = (\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, P)$$

where $P = \Pi_L$, $\mathcal{F} = L(\mathcal{A})$ and $(\mathcal{F}_t)_{t \geq 0}$ is the filtration obtained from $(\mathcal{A}_\tau)_{\tau \geq 0}$.

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(c) the equation for $u(t, \omega)$ holds for **all** $T_0 \leq T$.

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1. No need for limiting arguments and specialized compactness theorems to get a convergent subsequence from a sequence of finite dimensional Galerkin approximations. In fact the specialized compactness theorems (and the appropriate topology) are discovered as by-products.
2. The richness of Loeb spaces means that all activity can take place in a single underlying probability space - not only convenient but essential for formulating some ideas - eg process attractors and optimal controls in 3D.