"Second Theory": A Novel Innovation Enhancement Methodology

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Abstract--**One of the most potent failure factors for innovative projects is the human tendency to hold on to the original theory of the matter at hand. Early on when few relevant facts are known, the human mind comes up with a theory to explain the situation, and this theory, psychologically, subsequently amplifies every supportive new fact, and all the while suppresses every new fact that is inconsistent with this early theory. The net result is that the innovator holds on to a debunked theory. This leads to a long and costly R&D pathway that ends in an impasse.**

The "Second Theory" methodology calls for the researcher to come up with a second theory of the situation, a theory that is incompatible with the prime theory. The methodology then calls for the formality of 'pro' and 'con' arguments for both theories, and for an update of these arguments in light of new insight gained throughout the progress of the innovative effort. This procedure helps the innovator to remain objective between his early adopted 'pet theory' and the alternative theory that may gain weight given the newly discovered insight. A 'third theory' and a forth one, may be called for, depending on the complexity of the matter, and on the size of the innovation team.

Often times the two or more leading theories remain in play, and no single theory dominates. In that case one would practice several optional mathematical protocols to "fuse" these theories into a useful co-existence. Three such protocols are offered here: probability based resolution, dimensionality based resolution, and validity distribution scale.

I. INTRODUCTION

A new reality has emerged in the global innovation-driven economy: the Internet levels the playing field, and gives everyone the same reading as to what is needed next, in terms of technological solutions. This creates a situation where many teams around the globe are racing to develop the coveted solution, to rip the benefits of being first. While before it was important who can see what is needed next and develop it, today, what is needed is more obvious, and the race is simply on speed: *who will get there first*. See [19] "Innovation and Competitiveness" and [17] "Faster Value Creation".

This reality of the *'winner take all'* is putting a prime on innovation efficiency. It has been established long time ago, that innovation is a zigzag track, inherently. One takes a path, invests money, time, talent, and then hits an impasse, and a U-turn is called for, another choice is made, may be one or more impasses are encountered, until the right track is being spotted. We all do that, the question is how to minimize the zigzagging, how to shorten the overall innovation pathway, and win the race for the innovative result.

The history of science has shown that one of the most powerful tools innovators have in their toolbox is the notion of a *'theory'*. Human beings faced with a bunch of related facts on any given matter, routinely build a theory as to what generates these facts, how they come about – a story that relates this fact to a unity. A theory of science has two competing origins, or causes. On one hand, it is an explanation for *how things are*, motivated by our philosophical desire to grasp and understand the reality around us. On the other hand it has a utilitarian origin, it is a tool for us to first remember, then co-consider the related facts, and finally suggest more facts to be tested, using the method of science. The first motivation cares not for *what works*, but for *what is,* and the latter could not care less if a theory is correct, if it describes things *as they are*, or simply is a tool to effectively discover new facts, that can be verified by experiment.

Science and philosophy are still smarting up from the fundamental shocks of 20th century physics. One of the most unsettling recognitions is the '*duality*' of electromagnetic waves and corpuscular identity. Both theories of light (wave and matter) were unimpeachable, and this famous realization only led to more and more strange experimental phenomena that kept the two incompatible theories with full robust validity. People joked that light is corpuscular on even days, and a light-wave on odd days... But this was a nervous laughter, of the embarrassed.

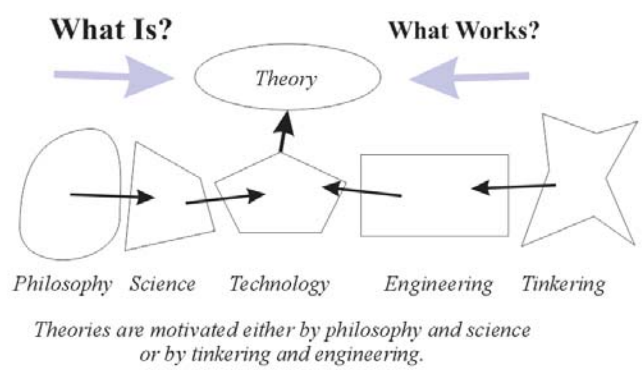


Figure 1 Origins of Theories

Eventually physics overcame this vexing realization with the help of formal mathematical treatment that managed to accommodate the apparently irreconcilable theories of matter. Neil Bohr famously said that science and physics don't share the philosophical desire to define what is, to describe the objective reality. Science is an attempt to put order in what we can measure. Science has no interest beyond the scientifically measured phenomena. Richard Feynman asserted that no one understands quantum mechanics, but its mathematical structure is very effective as a predictor of a result. "The atoms or elementary particles themselves are not real; they form a world of potentialities or possibilities rather than one of things or facts." – Werner Heisenberg.

The lesson from this startling reality is that in modern day science a theory is viewed as a utilitarian tool. In other words, *engineering trumps science*. The drive to find out how to make things work defeats the drive to find out how things are.

This demotion of the status of theory does not sit well with human psychological tendency to view one's theory of a situation as a description of how the situation really is beyond the data, the facts, and the reading. There are Darwinians explanations to it -- we are an explaining species. Presented with a set of related facts we quickly form a theory as to what stands behind these facts, and how they are related. These naturally and fast occurring theories dig themselves a deep groove into the scientist's psyche, and are hard to dislodge.

The impact of emotions, and interests on the acceptance of theories may at times rise to extremes. Formerly respected scientists, under pressure from the Nazi regime have concocted tortured theories as to the superiority of the Aryan man, and the inferiority of the Jews, the Slavs, and the Africans. More recently the "Hockey stick controversy" has flared up where reports by the Intergovernmental Panel on Climate Change (IPCC) alerting against the threat of man-made global warming, have been violently opposed by climate change deniers, assembling the same set of basic facts into the opposite conclusion. McComas [20] asserts that all knowledge in science is tentative. Merim Bilalic and Peter McLeod [21] conclude: "*While we are working through a problem, the brain's tendency is to stick with familiar ideas, can literally blind us to superior solutions*"

There are ample stories how false theories, prevailed in front of mounting evidence to the contrary. Psychologists have found that we naturally uplift any fact that supports our beloved theory and suppress the ones that disprove it. The net result is that a researcher and a developer (an R&D person) will defend his original theory, and as argued above, will create a wasteful zigzag path, that might cost his R&D team the win in the race.

This article offers an operational solution to this tendency. See Ref 1,2,3. for further discussion, and see Ref 4-13 for a sampling of today's literature on the topic of innovation and productivity.

II. HOW TO UNSEAT A NON-PRODUCTIVE THEORY

We have seen that non-productive theories lead the researchers and the developers down a wrong and wasteful path. And we also concluded that researchers and developers tend to embrace non-productive theories they conceived of early on, and rationalize their efforts. Trying to counter this practice of inefficiency, we propose a multi-stage plan:

- Adoption of the Sub-Theory concept
- Applying the 2nd theory procedure
- Modeling the Theory Space

We explain these stages:

A. The Sub-Theory Concept

We first define the concept of research & development domain (R&Dd) as the set of all independent facts that are relevant for the construction or the implementation of a device, a procedure, a tool. The right theory for that domain is the 'story,' the 'explanation' that allows for quick and efficient calculations relevant to the target construction or the target implementation. Our first operational assumption is: *Operation Assumption #1: the right theory can be identified only if the R&D domain is fully known, namely all the relevant independent facts are known.*

In the event that only a subset of the R&D domain is known, then the theory that can be expected is a *sub-theory* relative to the right theory because it is put together on the basis of only some, and not all of the relevant facts.

We now define a ' *useful sub-theory'* as a sub-theory that (i) makes the relevant calculations more efficient, or say, concluding the required answers more expediently, and (ii) helps one discover the missing facts of the matter. And hence, a non useful theory, or, say, a useless theory, is one that neither makes calculations more efficient, nor does it help discover the missing relevant facts of the matter.

Note: these definitions need to be internalized because by nature or by education scientists are disposed to rank theories according to the intellectual satisfaction one derives from them. The ingrained belief is that a theory should be faithful to the objective description of the situation. The practical, engineering (*not scientific, not philosophical*) approach ignores the question of fidelity to the matter as *'it really is'*, and ranks theories strictly by order of usefulness as defined above.

Let us now chart the theory progression chart, which is a chart that assumes that: (2^{nd} operational assumption:) *Every subset of the R&D domain corresponds to an unbiased sub-theory.*

The notion of unbiased sub theory refers to a theory that takes all the facts in the sub domain with equal weight, and fair impact.

For an R&D domain that contains n facts there are $n!$ orders of these facts. If we take one of those orders, we may ask ourselves what will be the unbiased theory that corresponds to the first $m < n$ facts? If we allow m to slide from $m=1$ to $m=n-1$ then we will identify, at least in theory, (pan intended), $(n-1)$ unbiased theories. And in total the R&D domain may be associated with $(n-1)n!$ unbiased theories, all less complete than the right theory (which is the same as the unbiased theory for $m=n$).

Given human nature, it is clear that no one is likely to develop the unbiased theory for any real life case where m, the number of available facts, is large enough. The human psyche is not built to regard a large number of facts fairly. We naturally emphasize some facts and de-emphasize others. We tend to ignore some facts that are formally known to us, if they are part of a large pool of facts. Hence several R&D experts looking at the same situation will regard a different subset of the relevant facts, and develop a different personal theory with some similarities and some dissimilarities with respect to the unbiased theory.

This analysis leads to an important conclusion: *an R&D person in any given R&D project will at best develop a sub-theory that approaches the corresponding unbiased theory*. Once this realization takes hold, it banishes the natural disposition where a theory is regarded as the faithful description of the matter as it is. And one is further conducive to the recognition that the current theory is a sub-theory that needs to be upgraded. The next conclusion, (central to this thesis), is that the upgrading of a sub-theory should take place by super-imposing it with a competing theory that draws its definition from a different set of facts, and is as much distinct and incompatible with the theory at hand. It amounts to applying the procedure (so well defined by Hagel), of a thesis cast together with its anti-thesis to form a better than both -- synthesis.

In a team environment that anti-thesis to a given thesis may be naturally found in the opinion of someone else in the team. But in a small team, and in a team with groupthink, as well in the mind of an individual innovator, there is a need to proactively identify a second theory that is as far as possible (and still credible, and supportable) from the first theory.

B. Applying the Second Theory Procedure

The Second Theory Procedure calls for a researcher and developer to identify a second theory that is as distinct and incompatible with the leading theory for the matter at hand. This can be done by imagining an input like this (from a recognized authority): *“Mr. or Ms. R&D person, we herewith tell you officially that the theory you suggested to explain the situation at hand is a bad theory, it does reflect the reality of the situation. Therefore we ask you to come up with a second theory, distinct and incompatible with the present one, and offer it to us"*. In some cases it would be easier to tap another person, not yet contaminated with the impression of the leading theory, and ask him or her to suggest a theory. The first, or second such extra source, might suggest the same theory raised by the R&D expert, but sooner or later a maven will be found that suggests a completely different theory.

This step of suggesting the 2nd theory may be the most difficult step because psychologically one is wedded to his pet theory and is disposed to reject and pooh-pooh anything incompatible with it. [21].

Having identified the 2nd theory, the next step is to prepare a table of pro and con arguments for each theory.

The third step amounts to rank-ordering the pro and con arguments according to the impact they have on the decision which theory to regard as the leading one. The easiest way formally to compare the two theories is to assign weights (a_k to argument k)to the various arguments. In that case one could easily compute the relative acceptability of each theory:

$$A = \Sigma a_i - \Sigma a_j$$

where *i* runs over the pro arguments for the theory, and *j* runs over the con arguments for the theory. Then one compares the *A* (acceptability) value for each theory, and the theory with the highest *A* value is the one regarded as the "leading theory".

The weak point for this procedure is that the weight assignment for the pro and con arguments are rather arbitrary, and in some instances, a slight change in their values will shift the title of leading theory from one to the other.

The standard way to increase the validity of the weight assignment to each argument is:

1. *Assign the weights with maximum separation from the theories themselves*
2. *Poll a large number of people, and statistically integrate the results.*

The arguments by which to sort out the theories may be defined, and weighted according to generic understanding of the situation and its objective, without any knowledge of the theories themselves. That way the weight appraiser is not influenced by the nature of the theory he or she ranks. For example the argument of simplicity -- preferring simple theories -- can be weight-assigned without regard to the nature or simplicity of the sorted out theories. The same with respect to compatibility of prevailing theories in near by fields, or with ease of corresponding computation, and with cost to verify, etc.

Another option is to pull back from this arbitrary assignment of numeric weights to the pro and con arguments. One would only rank-order them as to which argument should count more than which others. One such method, BiPSA, [1] documents how to apply this to the case at hand.

Since the 2nd theory was squeezed "by force" it would usually rank lower than the first theory, which will remain the leading one at the onset. However, as the R&D process continues, more and more facts are being revealed, and as it is likely to happen, both theories grow further from the unbiased theory associated with the new totality of known facts, and it might so happens that the first theory falls out of favor faster than the other. Over time, then the ranking between the theories might flip, and the 2nd theory will dictate the efforts to verify or use its conclusions in building the objective construct of the R&D effort.

C. Modeling the Theory Space

Given the existence of two (or more theories) to explain a given set of facts (a sub R&D domain), one faces three options:

1. To regard only the more favorable theory
2. To regard the two theories in tandem
3. To disregard the two theories, and attempt to discern a third theory

Options one and three are natural choices in extreme situations. If the acceptability grade (the *A* values) of the two theories are much apart $A_t << A_l$, where the index *l* reflects the leading theory (with the highest *A* value), and the index *t* refers to the trailing theory (with the lower A value), then it is natural to disregard the *t*-theory and regard only the *l*-theory.

If, the two competing theories are of nearly equal ranking, and are profoundly incompatible, it would stand to reason to scratch them both, and construct instead a third theory for which the challenging theory would be of a much lower acceptability value.

The option to fuse the two theories is the one that reflects the development of the present theory of quantum mechanics, and the mathematical formalism used so successfully there is a good start to apply in the general case of fusing two competing theories in the case where either one of these theories is of non-negligible acceptability.

Following the QM lead, we propose three mathematical approaches to fusing two theories:

- Probability Fusing
- Dimensionality Fusing
- Validity Distribution Scale fusing

And a fourth, which is a combination of these distinct options. The first mathematical formalism is based on probability calculus, the second on increasing the dimensionality of the feature space that describes the situation, and the third calls for devising a scale on which one would mark interval where different theories prevail.

1) Probability Based Fusion Of Competing Theories

The fundamental premise of this formalism is the following fact:

Basic premise of probability fusion: Given a theory f: $y = f(x_1, x_2, \ldots\ldots x_n)$

that combines n x factors to infer a dependent value y, it is always possible to replace this statement with: $y = f_p(x_1, x_2, \ldots\ldots x_n)$ where f_p is a delta shaped probability curve posted on the y value that is computed by f.

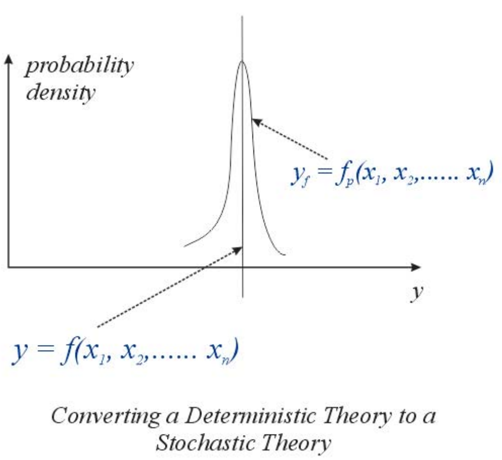


Figure 2 The Delta Function Replacement

The rational for replacing a deterministic theory with a stochastic one is simple and straight forward. No matter how many tests were made and shown to fit the f theory, that number of experiments is finite, and as such it could have been too low a number to show a result for y that is different. Once we conduct more experiments we will flash out the deviating results that would justify the probability version of the theory.

Come to think about it, this argument is unassailable. The delta function may always be set to be so narrow around the expected value that the current number of experiments will be too small to prove the probabilistic nature of the theory. Much like one who polls 1000 lottery players and concludes that there is zero chance to win the lottery since none of the polled people won the big prize -- ever!

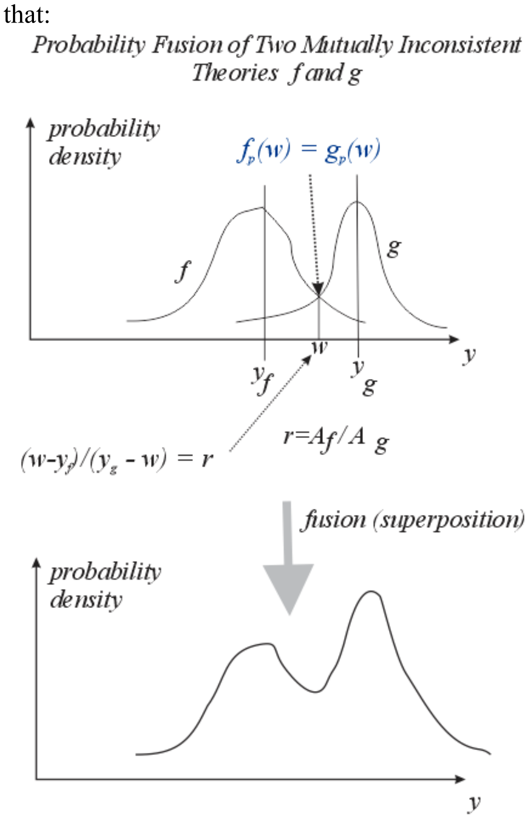
Let's consider a case where two theories f and g are both non-negligible, namely their acceptability values are: A_f, $A_g >> 0$, and let $r = A_f / A_g$ be the ratio of the acceptability ratios. These two theories are expressed relative to a set of n factors $x_1, x_2, \ldots. x_n$:

$$y = f(x_1, x_2, \ldots\ldots x_n)$$
$$y = g(x_1, x_2, \ldots\ldots x_n)$$

One way to fuse these two theories probability-wise is to replace the two functions with corresponding delta functions:

$$y_f = f_p(x_1, x_2, \ldots\ldots x_n)$$
$$y_g = g_n(x_1, x_2, \ldots\ldots x_n)$$

Such that:



$$\int_{-\infty}^{+\infty} y_f \, dy = kA_f \quad and \quad \int_{-\infty}^{+\infty} y_g \, dy = kA_g$$

Figure 3 Fusion of Theories

Where k is adjusted to insure that the sum of the integrals above is 1. This setup will then be used as a combined theory, (combined probability curve). Mathematically the sum of these two stochastic variables will define a y_{fg} curve that would yield numeric result representing the relative weights of the competing theories.

A second method is to define a point w such that: $y_f < w < y_g$ assuming $y_f < y_g$, and set w to satisfy: $(w-y_f)/(y_g - w) = r$ and then define two probability functions f_p and g_p as normal distributions such that their values at point w will be the same: $f_p(w) = g_p(w)$

So that the greater the acceptability of a theory, the more narrow is the normal distribution associated with it.

2) Dimensionality Based Fusion Of Competing Theories

Dimensionality fusion is hinged on the idea that a features space of dimensionality n can be expanded to dimensionality $n+1$, where the $n+1$ dimension is added to settle the disputed results between competing theories. We shall view the basic mathematical procedure, and then discuss the hierarchy case.

Let f and g be two conflicting theories that compute a dependent variable y from independent variables: $x_1, x_2, \ldots x_n$:

$$y_f = f(x_1, x_2, \ldots\ldots x_n) \neq y_g = g(x_1, x_2, \ldots\ldots x_n)$$

We may define an $n+1$ dimension, designated as z, and write:

$$y_f = f_z(x_1, x_2, \ldots\ldots x_n, z)$$
$$y_g = g_z(x_1, x_2, \ldots\ldots x_n, z)$$

where f_z and g_z are a modification of f and g respectively.

The added dimension z is independent of the other n, and is defined as the *'next plausible factor'* of y. Elaboration: when one devises a theory to be used in calculating the value of some variable y, this theory identifies some n independent parameters that together affect the value of y. Albeit, one never knows for sure whether y is completely defined by the identified n parameters, or perhaps there is another parameter, that also has a say onto the value of y. Now suppose the theory builder is a student, and the professor informs her that she neglected to identify the $n+1$ parameter that affects the value of y. So informed the student will venture her best guess as to the identity of the neglected parameter. Her guess is what z is: it is the most likely overlooked measurable and well defined parameter that may affect the value of y. After all, if two theories clash, they may both miss an impactful parameter.

One could now seek to modify $f \rightarrow f_z$, and $g \rightarrow g_z$, such that $f_z \rightarrow g_z$. In the case where there exist plenty of data where one measured y and measured the $n+1$ parameters that are to determine the value of y, then one could check the validity of the newly devised f_z and g_z, and refine their definition to increasingly fit the data at hand.

In the case where data is scarce, one could validate f_n and g_n by their increased proximity, or say by how much they agree with each other. This technique can readily be extended to any number $t > 2$ of theories, the closer they get, the greater the validity they claim.

3) Hierarchy

The n independent variables that feature in the theory to compute y, may themselves be computed variables based on another theory which is taking as input some m variables, which in turn can also be computed from lower variables. Each of these theories may be processed with this dimensionality concept, and the number of added dimensions may be as the number of nodes in this tree of theories.

4) Validity Distribution Scale

The idea for this method is to devise a scale over which to mark intervals of zone where one theory prevails over the other. Once again, assume two theories f and g, a variable of interest y, and n independent variables $x_1, x_2, \ldots x_n$. Let us define a scaling variable z: $z = Z(x_1, x_2, \ldots\ldots x_n)$

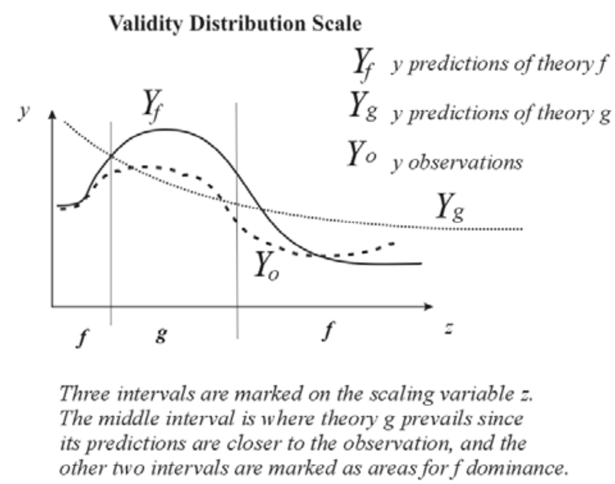


Figure 4 Validity Distribution Scale

And for every known data point compute the results given by the two theories (y_f, y_g) to be compared to the result shown from experimentation, or observation (y_e). The *gap* $|y_f - y_o|$ determines the weight of function f: $W_f(z)$, and the gap $|y_g - y_o|$ determines the weight of function g: $W_g(z)$.

Using any regression analysis of choice, the data points lead to some analytic functions: $W_f(z)$, and $W_g(z)$ for the range of z. Now for any desired combination $x_1, x_2, \ldots\ldots x_n$, one would compute f and g, and mitigate between them based on the relative values of the corresponding weight factors $W_f(z)$, *and* $W_g(z)$.

In the ideal case the z scale will have one or few intervals where f prevails, and the rest where g clearly is the valid theory.

III. APPLICATIONS

While most scientists in natural sciences officially agree that a theory is just a way to put order in data, and predict experimental results, and such, by deep seated instincts physicists and chemists when they devise a theory, they tend to believe that they describe things as they are, not just an ephemeral story which may be useful, but with little connection to objective reality of how things really are. That is why fusion of theories and the 2nd theory procedure are not very popular there. It is an irony though, that these techniques are inspired by the history of quantum mechanics, where perplexing issues like the duality of light, and other quantum phenomena that defy commonsense have been resolved through an elaborate body of mathematics, incorporating the methods mentioned here, especially probability and dimensionality.

The area where these techniques are readily acceptable are those areas where the prevailing theories are admittedly very arbitrary, and of a very low chance to describe the objective reality. Many issues in engineering, say, for example chemical engineering are based on formulas that have been developed from experience with no scientific foundation. Take for example the use of Reynolds number to predict flow pattern whether laminar or turbulent. The theory is observational, with no justification in known principles in physics. When it comes to softer sciences, the case is more pronounced. In psychology, sociology, marketing, etc. the formulas and the theories are many and each has typically a range of applicability. In these cases the procedures and tools discussed here are of great use.

IV. ILLUSTRATION

A membrane based filtration process, successfully tried in bench-top mode, and in low scale pilot, has disappointed when scaled up to production levels. The engineer in charge had recent experience with up-scaling difficulties that emanated from size sensitive flow regimen. Scaling up fluid flow systems do bring non linear issues with laminar versus turbulent flow. Accordingly, the engineer proposed the theory that implicated the flow pattern as the cause for the inability of the large scale system to separate between the solution ingredients. This theory led to solutions which featured larger scale membrane surface to accommodate slower fluid velocities. The problem became worse! A lot of time and money was spent on tinkering with the system based on the flow regimen theory. There was no attempt to use the "2nd Theory" procedure here described. Only late in the game, and after much frustration, a junior technician proposed a competing theory: the membrane at large surface area experiences tearing stress that results in small tears where the out-filtered ingredient sneaks through. Further experiments validated the challenging theory, and led to a satisfactory solution of the problem. The entire R&D operation would have finished much earlier, and cost less than half that it actually cost, if the team had practiced the 2nd Theory procedure recommended here.

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