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# SIMULATION-BASED DESIGN OF THE LENR SYSTEM

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## ABSTRACT

The Information Universe (IU) communicates with the Material Universe (MU) to create and repair atoms. This is required because quarks and bosons that make up atoms have a relatively short life and must be replaced. The communication messages are described by a context-sensitive language specified using message generating rules. The SUSY (Supersymmetric) inversion model is a process defined by these rules that describes how subatomic particles are made and combined to create or repair atoms; indeed, there is a language message (a sequence of process actions) for every IU/MU system regulatory problem. An OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of the IU/MU system can learn these rules to gain an understanding of the SUSY messaging process. The IU/MU system simulation model will also be used to learn and generate messages that result in the LENR (Low Energy Nuclear Reaction) system producing useful new physics.

## 1 INTRODUCTION

### 1.1 Entropy

In Shannon's information theory, entropy is a measure of information content for a set of messages such as between the Information Universe (IU) and Material Universe (MU). The IU/MU system model consists of a network of IU intelligent agents, that cover the MU on the Planck scale and communicate globally, such that several agents contribute to solving some MU regulatory problems. The agent communication messages are described by a context-sensitive language specified using message generating rules. The SUSY (Supersymmetric) inversion model is a timed process defined by these rules that describes how subatomic particles are made and combined to create or repair atoms; indeed, there is a language message (a sequence of process actions that occur at critical times) for every IU/MU system regulatory problem required to be solved by intelligent agents. The goal of the IU/MU system regulatory process is to maintain global charge balance and minimize energy consumption throughout the MU while creating or repairing atoms or solving other disturbances.

If all messages in a system are equally likely, then entropy is maximum. In a system under regulation such as the IU/MU system, most messages cannot occur, and entropy is low. The result of the IU/MU system regulatory process is low entropy (Clymer 2009). An example OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation demonstrates entropy reduction during the regulatory operation of a fuzzy traffic control system (Clymer et al. 2017).

### 1.2 OpEMCSS Systems Design Model

The OpEMCSS system design model (Clymer 2009) allows alternative system design concepts to be visualized as solutions to the systems design problem. The model is expressed using a diagramming method that describes a set of process threads (a sequence of states and events) that communicate and interact to implement system operation. These process threads are described using a set of graphical icons that can specify all concurrent, parallel processing operations; indeed, this graphical diagramming method defines **What** the system does to achieve system design goals.

To make this model executable to explore system behavior in its operational environment, an OpEMCSS system simulation program is required. The model icons are implemented using a set of program blocks (Clymer 2009) that eliminate most of the programming effort required to create an executable model. The blocks also allow executable models of alternative physical system designs that simulate the details of **How** the system may achieve system design goals.

### 1.3 Applying the OpEMCSS Simulation Process Diagram to the IU/MU system

Applying the OpEMCSS simulation program (Clymer 2009) to implement the OpEMCSS systems design model of the IU/MU system, intelligent agents are required to learn and execute regulatory actions. A sequence of agent actions is called a process. The agents are simulated using the OpEMCSS, Classifier System block. There is one agent for each 3D point in the MU. Each agent has multi-dimensional and instantaneous information channels with other agents throughout the IU (Clymer 2009). During IU/MU system operation, intelligent agents communicate and interact; indeed, the SUSY inversion model describes the subatomic particle creation and regulation process to produce stable atoms and solve other regulatory problems.

### 1.4 IU/MU System Design Diagram

Examining the OpEMCSS system design diagram of the IU/MU system in Figure 1, the Classifier System block learns the rules needed for IU intelligent agents to communicate to regulate the MU. Such regulation is a sequence of timed actions (a process) where agents communicate and interact with other agents using rule-based language as discussed above. Rule learning requires a utility function that is a measure of performance for the agent regulatory actions, often involving a sequence of such timed actions requiring the Classifier System to perform reinforcement learning.

### 1.5 LENR System Design

The LENR (Low Energy Nuclear Reaction) "physical" system, described later in this paper, consists of a computer, a controllable information wave (Franceschetti 2018) light signal source to generate SUSY timed process messages, and quantum state sensors to measure the effects of LENR system control actions on achieving system goals. The LENR system goal is to maintain continuous LENR system operation to produce desired new physics such as reduced gravity, electric current, photon production, or temperature control. To achieve these goals, the LENR system computer sends regulatory messages to target MU matter, based on learned SUSY timed process rules, to create disturbances that destabilize local IU/MU system operation. Non-stable isotopes are created and maintained that have the desired properties of the new physics. It is important to understand the IU/MU system regulatory process before trying to safely create LENR system disturbances in the MU to produce new physics. Therefore, LENR system experiments are envisioned to demonstrate these effects can be safely produced.

The SUSY (Supersymmetric) inversion model is a process defined by message rules that describe how subatomic particles are made and combined to create or repair atoms; indeed, there is a language message (a sequence of timed process actions) for every regulatory problem. An OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of the IU/MU system can learn these rules to gain an understanding of the SUSY messaging process. For the Classifier System to learn such rules, features defining current system state and utility function values that measure how well the rules achieve system goals are required. These are discussed in the next section.

LENR system physical operation will provide the quantum state sensor data: (1) to measure the effects of LENR system control actions needed to provide the utility function and (2) rule features defining current subatomic state of the message process. Initial experiments will explore the creation of hydrogen atoms where the SUSY inversion model is best understood. Future experiments will explore more complex atoms as further understanding of SUSY inversion model is gained. The goal of the LENR system is to produce desired new physics as discussed above.

### 1.6 Summary

Described in this paper is an OPEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of IU/MU system operation that learns rules that can select regulatory actions in response to quantum level disturbances in the MU. The OpEMCSS simulation program also supports the design and development of the LENR physical system to maintain regulatory actions in the MU that achieve continuous production of desired new physics.

## 2 OPEMCSS IU/MU SIMULATION AND RESULTS

### 2.1 Overview of the IU/MU System Process

Reference (Meijer 2020) is an outstanding tutorial of a large body of research on the nature of quantum physics, human brain consciousness, and fabric of physical reality as related to the IU/MU system. For this paper, the Information Universe (IU) is described as a collection of concurrent, communicating process threads executed by a network of intelligent agents where each thread decides the next quantum state of a local particle of matter in the MU. Each one of 1000 duplicates (Clymer 2009) of the quantum process threads, shown in figure 1, is a sequence of states and events that model the IU/MU interface to the 3D MU space.

Viewing the IU/MU system operation, OpEMCSS diagram in Figure 1, only one thread is shown, but it is duplicated 1000 times, making the number of threads in a process very flexible. Each duplicate quantum process thread determines the current quantum state of matter under its control. Next, rules that are global to the entire universe, are applied to determine the next quantum state regulatory action. Finally, all quantum process threads synchronize and share information globally to learn new rules. In IU quantum time, this quantum state processing is called a "blink." Paper (Meijer 2020) discusses many ideas about how these processes might be implemented. However, in this paper, an OpEMCSS simulation program is used to explore the learning of global decision-making rules for the IU/MU system. The results show that entropy is reduced while atomic, quantum particles are turned into mostly hydrogen atoms given the utility function described in (Meijer 2020).

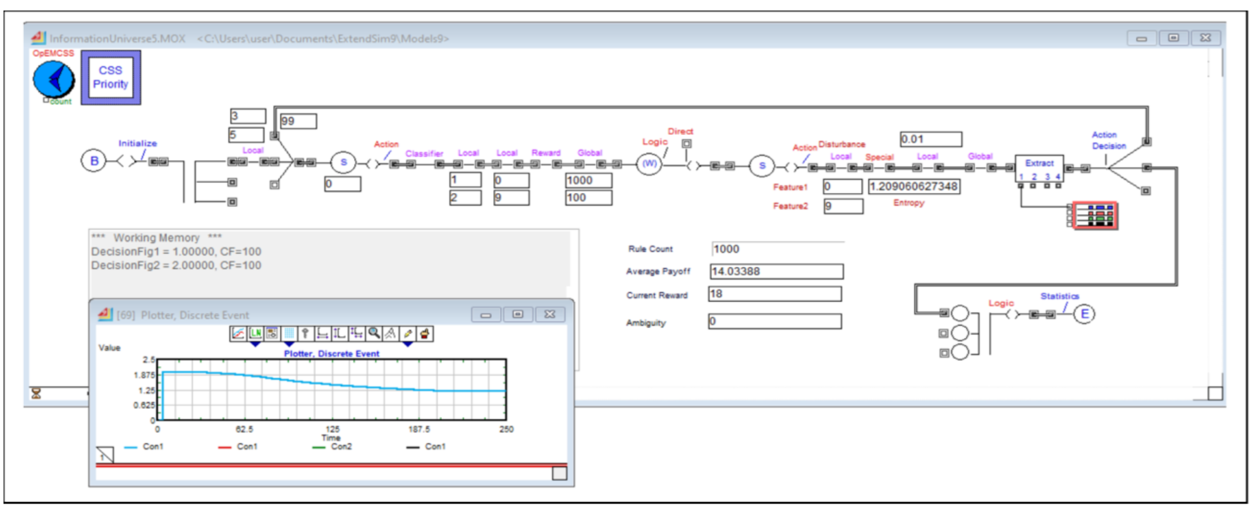


Figure 1: OpEMCSS simulation model diagram

### 2.2 OpEMCSS Blocks Used

Figure1 shows the OpEMCSS simulation model diagram that plots entropy as rules are learned. The Wiley Systems Engineering and Management text (Clymer 2009) provides a detailed description of what all the OpEMCSS blocks do and how they are connected. Basically, the connected blocks describe a simulation program where 99% of simulation programming is performed by the blocks and only process thread logic and other operational details must be coded. Coding operational details is required to create an executable system design model instead of just a non-executable system diagram (Clymer 2009).

The Begin block on the left side of the diagram creates the initial process thread and loads variable values provided in the block dialog. The next block splits the initial process thread into a 1000 duplicate, concurrent process threads that all execute the process diagram shown. The quantum state, as shown in Figure 2, is represented by two feature facts (Meijer 2020), obtained from the MU, each having 10 possible values. The LENR system simulation program will have feature facts based on the SUSY inversion model which requires a sequence of messages and reinforcement rule learning discussed below. Figure 2 shows part of the agent's rule definition file that is loaded into the Classifier System block at the beginning of a simulation run. Given the feature space shown, a quantum state could be one of 100 possible combinations of Feature1 and Feature2.

```
LegalConditionVals(Feature1)=A(0:0),B(1:1),C(2:2),D(3:3),E(4:4),F(5:5),G(6:6),H(7:7),I(8:8),J(9:9)
LegalConditionVals(Feature2)=A(0:0),B(1:1),C(2:2),D(3:3),E(4:4),F(5:5),G(6:6),H(7:7),I(8:8),J(9:9)
LegalActionVals(DecisionFig1)=IncFIG1(1:1),DecFIG1(2:2),FIG1(3:3)
LegalActionVals(DecisionFig2)=IncFIG2(1:1),DecFIG2(2:2),FIG2(3:3)
```

Figure 2: Agent rule definition file.

Figure 3 shows one of the ten initial rules to begin rule learning. There is one rule for each possible value of Feature1. These rules are modified and expanded during rule learning by the Classifier System block. When a rule fires (selected for action execution) the quantum state is changed according to the rule action. If rule 1 in Figure 3 fired, Feature1 value A (0) is incremented to value B (1).

```
Rule 1:IF
     Feature1 = A,
THEN
     DecisionFIG1 = IncFIG1, CF=50.0%
```

Figure 3: An example of an initial rule to begin rule learning.

The Reward block applies the utility function, (PayoffOUT = 2*ABS(Feature2 – Feature1), to compute a new value for the Confidence Factor (CF) of the fired rule (Clymer 2009). The CF value is part of the calculation to decide which applicable rule is selected to fire. This utility function was provided in (Meijer 2020) which favors quantum states [0,9] or [9,0] for hydrogen.

The Wait Event block has logic that causes all concurrent process threads to synchronize so that they all contribute to rule learning at the end of a "blink." The Special entropy calculation block updates a 10 by 10 Memory matrix that counts the occurrence of each quantum state and counts each trial, NumTrials. Probability of a quantum state occurrence P equals Memory[i][j] / NumTrials for each quantum state [i][j]. Entropy is summation of -P*Log10(P).

The Extract block obtains the value of entropy and sends it to the plotter block. A plot of entropy as rule learning proceeds is shown in Figure 1. Entropy decreases as rule learning proceeds and quantum states [0,9] or [9,0] become the most likely.

### 2.3 Disturbance Required for Rule Learning

A probability of disturbance (Pdisturbance = 0.25) was added to the simulation so that during the synchronized global part of the "blink" period, each concurrent process thread is selected at random for change. If selected, Feature1 and Feature2 are changed randomly to one of the possible 100 quantum state values. Therefore, each quantum process thread has a 25% chance for a random change of quantum state at the end of a “blink.” This was done to simulate chaotic conditions that constantly disturb the Material Universe (MU) and thus require regulation. Shown in Figure 1 is one experiment where Pdisturbance started at 0.25 and was reduced in steps of 0.001 until 0.01 was reached. The plot shows entropy reduction as a function of number of “blinks” while Pdisturbance is reduced.

During model development it was observed that when probability of disturbance was zero, the rules produced did not work, in subsequent runs, once rule learning was initially complete. This problem occurred because the system would converge to quantum states [0,9] and [9,0] and no further change was possible even though disturbances in the MU are ongoing. The lesson here is that some level of disturbance is required to learn and maintain the permanent rules needed to achieve the desired quantum states in the presence of MU tendency to disorder. The model version shown in Figure 1 includes the reduction of Pdisturbance during rule learning. The smallest value entropy so far was achieved with this version: more than in Figures 4 and 5, below.

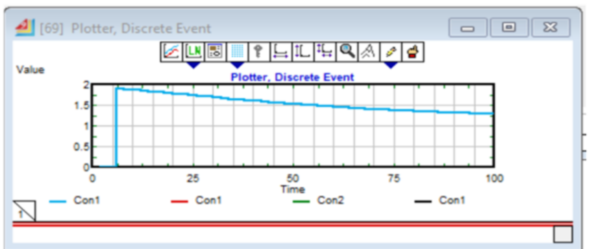


Figure 4: Pdisturbance of 0.2

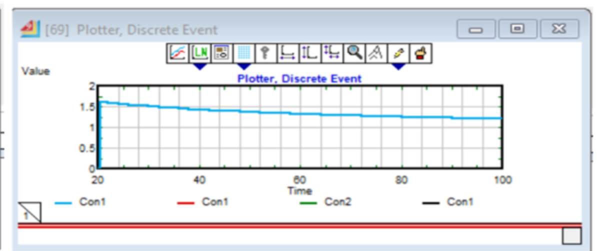


Figure 5: Pdisturbance of 0.05

### 2.4 How to Learn to Regulate All Atoms

Suppose the learned regulatory rules for hydrogen are made (ConstraintRules) rules, in the Classifier system block, that cannot change. Further, these ConstraintRules rules are used by the Classifier System in another experiment. In this experiment, the simulation starts with initial quantum states of all process threads in chaos. ConstraintRules do not take part in rule learning, but they always fire if eligible. New rules are generated, but they do not persist because the ConstraintRules for hydrogen are sufficient. However, if other atoms are included in the model plus the proper utility function, new rules that regulate these atoms would persist. Therefore, rules for all atoms of interest to the LENR system design (neodymium) could be obtained sequentially by adding to the ConstraintRules. Organizing the linear list of constraint rules into a rule hierarchy results in rules that execute much faster.

## 3 EVOLUTIONARY OPTIMIZATION OF LEARNED RULES

### 3.1 Classifier System Rule Learning Algorithm

The Classifier System algorithm discussed in (Clymer 2009), contains a forward chaining, inference engine that uses condition-action rules to transform condition attributes, obtained from feature facts, into action attributes that change system state. A utility function is used to measure how close each rule action achieves the goals of the system. These measurements are used to guide the evolutionary search algorithm to search through an extremely large rule space to discover a minimal rule set to make the best decisions. Evolutionary search algorithms are essential to ever reaching the goal of the LENR system design, continuously producing desired new physics, because system design search space is astronomical. It is important to distinguish the Classifier System algorithm used in the LENR physical system C++ software from the Classifier System block used in the OpEMCSS simulation program; however, they both work the same.

The condition attributes are obtained from a process thread passing through the block. After inferencing is complete, action attributes are added to the process thread before the item is sent to the next block. If several different rules are implied by the condition attributes (i.e., several rules are eligible to fire in a context), the best rule is selected based on either a maximum BID value or a rule selection probability. Maximum BID value is a function of rule strength, specificity (number of features), and condition support such that a more specific rule has a higher BID. Rule selection probability is a linear function of rule rank which is based on rule strength times percentage positive reward. Probability is used during rule learning and Maximum BID value is used when rule learning is turned off. Using a Maximum BID value, the result is that the most general rule that covers all situations correctly emerges as the best rule.

### 3.2 Reinforcement Learning

The Classifier System algorithm can also perform reinforcement learning, related to dynamic programming, to learn a sequence of rules that execute a plan. During reinforcement learning (Clymer 2009) to obtain a sequence of control rules, either maximum BID value or rule selection probability can be used during the generation of new rules. Rule selection probability allows all eligible rules a chance to specify the action attributes, but the highest ranked rule is ten times as likely as the least ranked rule to do so. This allows both exploitation of the current best rules and exploration for better future rules to occur concurrently. If the decision remains ambiguous, Maximum BID allows evaluation of alternative rules to fine tune decision-making performance. This can occur if the condition attributes are insufficient to unambiguously (Clymer 2009) classify all decision situations. Either maximum BID value or rule selection probability can be used after rule learning is complete; however, the maximum BID value is recommended.

### 3.3 Fuzzy Control

In fuzzy control of a system, the inference engine requires a Confidence Factor (CF) for each condition fact that depends on its value (Clymer 2009). If a condition fact has a ConditionFuzzySet definition command at the beginning of the rule file, the CF is computed using this definition. Otherwise, the fact is assumed crisp (CF is 100). The format of the ConditionFuzzySet command is as follows:

ConditionFuzzySet(AttributeName) = ValueName(A, B, C).

The fuzzy set function defined by A, B, and C has a trapezoidal shape. The top of the trapezoid ([B-A]) is smaller than or equal to the base (length [[B-A]+2C]). At the top of the trapezoid, the CF is 100. The A and B values define where the function begins a linear descent to zero. The C value defines the slope (100/C) of the descent. Thus, if C is zero, the trapezoid becomes a rectangle. If A equals B and C is not zero, the function has a triangular shape.

Fuzzy facts were used in the traffic model discussed in (Clymer 2017) to perform fuzzy control of a vehicle traffic control network that allows a non-linear system control surface to be implemented. In the operation of the LENR physical system, fuzzy control is an option to control the continuous production of desired new physics.

## 4 OPEMCSS SIMULATION OF THE LENR SYSTEM

### 4.1 Modification of the OpEMCSS Simulation Model

The OpEMCSS simulation program discussed above was created to implement IU/MU system operation described in reference (Meijer 2020). This model must be expanded to simulate the IU/MU system operation in support of the LENR physical system design.

The Information Universe (IU) communicates with the Material Universe (MU) to create and repair atoms or regulate disturbances in the MU. The communication messages are described by a context-sensitive language specified using message generating rules. The SUSY (Supersymmetric) inversion model is a process defined by these rules that describe how subatomic particles are made and combined to repair or create atoms or regulate disturbances in the MU.

In the current simulation model, the next quantum state of a hydrogen atom is decided in a single step given the current state. The time between message events is constant and the same for all agents; further, the agent processes synchronize after all agent actions have completed and share information globally to learn new rules, defining a "blink" as discussed in section2.

However, in the new model, a timed sequence of messages is required to make subatomic particles and combined them to repair or create an atom or regulate disturbances in the MU. Thus, because the SUSY message process proceeds in timed steps going from state to state where timing between events actions is critical, the message rules must be learned in stages forming a sequence of timed process actions where not only the action must be learned but also the timing of the action. To learn the sequence of message generating rules, reinforcement learning may need to be applied using the existing capability of the Classifier System.

Some of the model changes required are as follows. The agent rule definition file for the current simulation model, shown in Figure 1, that only provides the current quantum state, will be expanded to include six messages (feature facts), one from each of the closest agents in the three-dimensional space. An additional feature fact defining the current stage of the sequence will also be added. Further, a utility function based on the required quantum state and event timing for each stage will be included to guide the rule generation process.

The LENR physical system must provide sensor information to guide the learning of the message generating rules. First, this sensor information will be collected from the LENR physical system and analyzed to provide the IU/MU system simulation program with a numerical or mathematical model specifying values for the quantum state feature facts and utility function(s) for each stage needed to learn message rules. Knowledge gained from the IU/MU system simulation program will aid in gaining an understanding of the SUSY messaging process. Second, understanding gained through simulation will assist in learning the actual SUSY message rules, during LENR system operation, that is needed to produce new physics. The LENR system computer will apply the C++ version of the Classifier System program to learn the message rules in a manner like simulation. It is expected that this iterative process between the IU/MU system simulation program and LENR physical system operation will converge, providing working message generating rules to produce useful new physics.

### 4.2 LENR System Design

An OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of the IU/MU system can learn the message generating rules to gain an understanding of the SUSY messaging process. The IU/MU system simulation model will provide the rule definition structure discussed above. This rule definition structure will be used in the LENR C++ version of the Classifier System program to learn rules based on actual utility function and feature values obtained from quantum state sensors in the LENR (Low Energy Nuclear Reaction) system that continuously produce useful new physics.

During LENR physical system operation, the rule learning utility function(s) will be derived based on LENR system sensor measurements for each stage of rule learning; further, the current quantum state of subatomic particle creation and combination is required at each stage to provide feature fact values. These sensor measurements are input, via a numerical or mathematical equation, to provide the rule conditions, feature facts, to the Classifier System inferencing process. The condition-action messaging rules are learned and applied to implement rule actions that produce the next quantum state in the sequence. Guided by the utility functions, rule learning will evolve the correct quantum state sequence that results in the creation or repair of atoms or the regulation of other disturbances. The SUSY inversion model, message process is best understood for hydrogen which will make learning the message rules easier. The goal of the LENR system design is that the LENR system will eventually generate message sequences that result in the LENR (Low Energy Nuclear Reaction) system producing useful new physics.

## 5 MODEL OF SUSY INVERSION QUANTUM STATES

Supersymmetry (SUSY) is a model that suggests that every particle has an anti-particle that looks identical in all properties except one, they have opposite charges. The most obvious example is the (Pushp 2025) electron and the positron (Feynman 1949). The electron is the matter form, and the positron is the anti-matter form. Supersymmetry "inversion" (Toptani 2023) is like supersymmetry except that the pairing of matter and antimatter occurs in whole atoms. Atoms are half matter (proton and electron) and half anti-matter (neutron and positron). Atoms demonstrate Baryonic symmetry (matter and anti-matter are in balance) in the SUSY inversion model. The SUSY inversion model allows for the interchange of particles to occur between the nucleus and the orbital layers of atoms. In this model the electron and positron can become quarks in the nucleus of the atom. The electron negative can become the Down quark positive. The Up quark negative in the nucleus can become the positron in the orbital layer. The quarks in the nucleus of the atom can become an electron or positron in the LENR system process. This identity transformation takes place during LENR processes such as beta plus and beta minus decay. This change of particle identity involves the switching of charge. A positive charge becomes a negative charge, and a negative charge becomes a positive charge. A positive charge in the nucleus transforms into a negative charge in the orbital layer of the atom. A positive charge within the orbital layer of the atom converts into a negative charge in the nucleus of the atom. Such charge switching makes the system dynamic and responsive to internal and external charge distribution.

### 5.1 MODELLING USING SUSY INVERSION AND THE ATOMIC ISOELECTRIC POINT

The modelling of the LENR process of beta plus and beta minus decay looks at this exchange of charge states between the nucleus and orbital layers in atoms in the SUSY inversion model. Like a good accountant, the charge needs to be balanced. The overall charge of the atom prefers to be zero and this is the atoms isoelectric point (AIP). The isoelectric point of the atom is its most stable state. The isoelectric point of the atom is not the absence of charge, but a process where the atom reorganizes its structure to minimize charge through balancing positive and negative charges achieving charge cancelation. The stable state of the atom is achieved when the number of protons and electrons (matter charges) is equal, and the number of positrons and neutrons (anti-matter charges) is equal.

### 5.2 SUSY Inversion and Revision of Quark Charge Calculations

The inclusion of positrons in atomic theory is a fundamental difference in the SUSY inversion theory compared to standard atomic theory for charge. The positron inclusion is obtained by revising quark charges to either plus one or negative one. The charge switching between the nucleus and the orbital layers in the LENR systems modelling of processes can be followed more easily because of the revision of quark charges. The use of whole numbers (+1 or -1) and multiplication in SUSY inversion quark charge calculations compared to the usual approach of adding fractions (-1/3 or +2/3). Modifying the standard model (neutrons = 0 and protons +1) for atomic theory enables greater investigatory power utilizing the SUSY inversion quark charge calculation framework that corresponds to Baryonic symmetry.

### 5.3 SUSY Inversion and Baryonic Symmetry

The SUSY inversion model takes the fundamental position that Baryonic symmetry is the idealized approach that the universe uses to maintain charge conservation. The generation of entangled pairs of positrons and electrons is a charge conservation rule in SUSY inversion. An equal amount of matter and antimatter is generated by the universe. Whereas Baryonic asymmetry (Johnson 2025) (matter and anti-matter are not in balance) is our current standard understanding based on Big Bang hot nucleosynthesis (Schramm 1998). Baryonic asymmetry is assumed because of the scientific methodology involving measurement, and it is proposed to be an artefact of the biological observer and the basis for the observer's paradox in quantum mechanics. This limitation placed on matter comprising only 5% of the universe's composition restricts our ability to explain the initial structural features of the singularity at the beginning of time. This has hampered our understanding of the identity of dark energy (Carroll 2007) and dark matter (Jungman et al. 1996) that makes up approximately 95% of the universe.

### 5.4 SUSY Inversion and the Mathematical Calculation of Charges

The SUSY inversion model approaches these unknowns using the revision of quark charge calculations for protons ($-1 \times +1 \times -1 = +1$) and neutrons ($+1 \times -1 \times +1 = -1$). This approach sheds light on the unknown in a theoretical way, accounting for the issue of the missing anti-matter in cosmology and the horizon problem in cosmology (11). The features that arise from altering atomic theory (altered quark charge calculations), provide the basis for seeing a way to introduce Baryonic symmetry along with SUSY inversion as the basic framework for exploring the unknowns of the universe. By matching the revised atomic theory to the universe's composition, the identification of a process responsible for dark matter formation as its decay into the creation of positrons entangled to neutrons was identified. This creates a theoretical model that shifts the attention from the identified asymmetric state obtained through measurement into a symmetric state based on theory.

### 5.5 SUSY Inversion and the He-BEC Singularity

The SUSY inversion framework in its current form offers a solution to the initial state of the universe (He-BEC model (Pushp 2025) along with specific parameters that match atomic theory with the composition of the universe given an alpha particle emission process linked to the simultaneous generation of dark energy and dark matter (Johnson 2025). It also provides an explanation for cosmological inflationary parameters (Schramm et al. 1998) and the identity of dark matter and dark energy and several other aspects of subatomic features of atoms. It offers a way to explore the subatomic processes involved in LENR systems and their functionality in biological living systems (Toptani 2023).

### 5.6 SUSY Inversion and the IU/MU system

The SUSY inversion theory suggests that the Information Universe (IU comprising dark energy and dark matter made through alpha particle emission from the He-BEC isotropic singularity) implements a set of functional criteria that precursor engineers the MU (matter component of the universe). The SUSY inversion process and its initial characteristics such as radius, inner ground state wavelength, and alpha particle half-life timings have produced the foundations of space and time and acts as a house in which the MU matter universe may function. It explains how entanglement occurs connecting the IU and MU through the singularity at the center of the aromatic ring, surrounding the atomic nucleus, and why only a light information wave signal can carry the information required through the IU/MU interface to regulate matter in the MU. The rules of charge conservation and energy conservation provide a basis for the governance of the MU by the IU as the IU comprises 95% of the composition of the universe. It's form and function through Lorenz symmetry breaking initially from the alpha particle emission process from the He-BEC isotropic singularity offers an asymmetry whilst maintaining charge parity ($+1 -1 = 0$) and energy conservation due to the balance of outward v^2 and inward (√ v)^4 velocities.

## 6 CONCLUSIONS

The Information Universe (IU) communicates with the Material Universe (MU) to create and repair atoms or regulate other disturbances. This is required because quarks and bosons that make up atoms have a relatively short life and must be replaced. The communication messages are described by a context-sensitive language specified using message generating rules. The SUSY (Supersymmetric) inversion model is a process defined by these rules that describes how subatomic particles are made and combined to create or repair atoms; indeed, there is a language message (a sequence of process actions) for every IU/MU system regulatory problem. An OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of the IU/MU system can learn the rule definition structure needed to gain an understanding of the SUSY messaging process. The IU/MU system simulation rule definition structure will be used to learn and generate messages that result in the LENR (Low Energy Nuclear Reaction) system producing useful new physics. Initially, experiments to learn the rules to create hydrogen atoms will be done because this process is best understood. More complex atoms will be considered as understanding grows. The goal is for LENR system operation to be able to disturb IU/MU system processing to continuously produce useful new physics

### 6.1 OpEMCSS Simulation-Based Design of the LENR System

The OpEMCSS simulation-based design methodology (Clymer 2009) as applied to IU/MU system operation is a "way-of-thinking" about the conceptual operation of the IU/MU system required to solve the IU/MU system regulatory problem. An icon-based diagram, that represents all process threads required for concurrent, context-sensitive system operation, is created. The simulation program is developed from this diagram, and each process thread executes the states and events of the IU regulatory process. The simulation program includes intelligent agents, implemented using the OpEMCSS Classifier Block, that makes regulatory decisions affecting the Material Universe (MU).

### 6.2 SUSY Inversion Theory

The SUSY (Supersymmetric) inversion model is a process defined by message rules that describe how subatomic particles are made and combined to create atoms or regulate other disturbances. It explains how entanglement occurs by connecting the IU and MU messaging through the singularity at the center of an atomic nucleus. It also explains why only a light information wave (Franceschetti 2018) signal can communicate the information required through the IU/MU interface at the Planck scale to regulate matter in the MU. The SUSY inversion model requires instantaneous connectivity among agents throughout the IU to regulate disturbances in the MU. Further, time in the IU is an operator and proceeds in unequal steps as discussed for the IU/MU simulation model such that time in the MU appears continuous and linear but it approximates the IU process.

### 6.3 LENR System Design

The LENR (Low Energy Nuclear Reaction) system design includes a computer, a controllable information wave light signal source to transmit SUSY process messages, and quantum state sensors to measure the current quantum state (rule features) and the effects of LENR system control actions on achieving system goals (utility function values). The LENR system goal is to maintain continuous LENR system operation to produce desired new physics such as reduced gravity, electric current or photon production, or temperature control. To achieve these goals, LENR system operation requires computer generated message sequences, based on learned SUSY process rules, to select a sequence of optimal regulatory actions or messages to disturb the MU and produce useful new physics.

An OpEMCSS (Operational Evaluation Model for Complex Sensitive Systems) simulation model of the IU/MU system can learn these rules to gain an understanding of the SUSY messaging process. LENR system physical operation will provide sensor data, describing the SUSY inversion quantum states, to learn the SUSY message generation rules: measures the effects of LENR system control actions needed to provide rule utility function(s) and (Clymer 2009) feature facts defining the current quantum states of the message sequence. Initial experiments will explore the creation of hydrogen atoms where the SUSY inversion model is best understood. Future experiments will explore more complex atoms as further understanding of SUSY inversion model is gained.

## REFERENCES


Carroll, Sean 2007. Dark Matter. "Dark Energy: The Dark Side of the Universe". Teaching Company, LLC, ISBN1598033514, 9781598033519, p. 46.

Clymer, J.R. 2009. Simulation-Based Engineering of Complex Systems. 2nd ed. Hoboken, NJ: John Wiley & Sons Inc.

Clymer, J.R., and A.M.Vakil. 2017. "Exploring Combined Material and Information Universe to Discover New Physics", Available on Research Gate.

Clymer, J.R., 2017. "Simulation of a Vehicle Traffic Control Network Using a Fuzzy Classifier System". In Proceedings of the Advanced Simulation Technologies Conference (ATSC), April 14-18, San Diego, CA.

Clymer, J.R., 2017. “Mathematics of Complex Adaptive Systems”, International Journal of Design & Nature and Ecodynamics 12(3): 377-384.

Clymer, J.R., and A.M.Vakil. 2018. “Quantum Particle Regulation in the Combined Material and Information Universe: Simulation Model”, Available on Research Gate.

Clymer, J.R., and A.M.Vakil. 2020. “Evolution of Information Universe Rules to Regulate the Material Universe Quantum Stability: Simulation Model”, Available on Research Gate.

Feynman, R. 1949. "The Theory of Positrons". Physical Review 76 (6): 749–759.

Franceschetti, M. 2018. *Wave Theory of Information*, Cambridge University Press.

Gariaev, P.P, et al. 2011. “DNA as Basis for Quantum Biocomputer”, DNA Decipher Journal 1(1), 025-046.

Hill, V., and P. Rowlands. 2008. Natures Code, Available on Research Gate.

Toptani, A.S., and K. Johnson. 2023. In Proceedings of the LOPS (Laser Optics Photonics Sensors and Nonlinear Optics) Conference, June 2nd-5th, Florida, USA.

Pushp, A., and K. Johnson. 2025. “A revision of quark charge calculations using supersymmetry (SUSY) inversion framework and resolution of baryon asymmetry”. Journal of Quantum Physics Letters. QPL060125.

Johnson, K., 2025. “Presentation at the International Summit on Gravitation, Astrophysics and Cosmology”, March 13th-15th, Valencia, Spain.

Jungman, G., Kamionkowski, M., and K. Griest. 1996. "Supersymmetric Dark Matter". Journal of Physics Reports 267(5–6): 195–373.

Meijer, D. 2020. “A New Premise for Quantum Physics, Consciousness and Fabric of Reality”, Available on Research Gate.

Schramm, D. N. and M. S. Turner. 1998. "Big-Bang Nucleosynthesis Enters the Precision Era". Journal of Reviews of Modern Physics70(1): 303–318.

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