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Offset-Neutrosophic Upside-Down Assessment Model (ON-UAM): A New Way to Measure the Performance of Basic Education Informatization

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Abstract-In many countries, the performance of basic education informatization is measured using traditional methods that assume data is always correct, clear, and balanced. However, in reality, performance reports are often uncertain, exaggerated, or even misleading. This paper introduces a new model called ON-UAM (Offset-Neutrosophic Upside-Down Assessment Model) that helps measure education informatization more accurately. This model combines three unique ideas: (1) Neutrosophic Offsets, which allow values beyond the normal [0, 1] range to include overperformance and underperformance; (2) Upside-Down Logic, which helps detect and adjust misleading or biased reports; and (3) N-norm and N-conorm operations, which combine different performance indicators using logic that accounts for uncertainty and contradiction. We present mathematical equations and real examples that show how ON-UAM can evaluate informatization more realistically, even when data is unclear or manipulated. This method can help governments, schools, and researchers make better decisions based on more honest and flexible assessments.

Keywords: uncertain over-/under-/off-set/logic/measure/probability/statistics, education informatization, upside-down logics, truthification of the false, falsification of the truth, uncertainty, overperformance, N-norm, indeterminacy

1. Introduction

The use of digital tools, like computers, the internet, and online learning platforms, in schools is called "education informatization." It's a keyway to improve education systems worldwide. Schools and governments are adopting these technologies to make teaching and learning better in classrooms [1].

However, figuring out if these efforts are successful is not easy. Reports from schools or education departments might look good but may not tell the whole story. Sometimes, the data is incomplete, unclear, or even misleading. For example, a school might say it uses technology a lot, but it could lack trained teachers or working equipment [2]. In some cases, reports are shaped to look better than reality, often due to pressure from politics or funding needs [3].

Most traditional evaluation methods don't handle these issues well. They assume all data is either completely true or completely false, ignoring uncertainty or distortion [4]. To fix this, we need a better way to measure success that we can handle:

a) Confusing or incomplete information
b) Results that are much better or worse than expected
c) Data that might be misrepresented

This paper introduces a new method called the Offset-Neutrosophic Upside-Down Assessment Model (ON-UAM). It uses advanced logic to show:

a) How true or false the information is
b) How uncertain the data might be
c) When performance is unusually high or low
d) When results are distorted, like making false data seem true

This new approach builds on existing research to address these challenges [5]. In the next sections, we'll review what other researchers have found and then explain our new method using simple math and real-world examples.

2. Literature Review

Researchers have been trying to measure education performance for years using various methods. One common approach is fuzzy logic, introduced by Zadeh [6]. Fuzzy logic allows values between 0 and 1, so something can be "partly true" instead of just true or false. Later, Atanassov built on this with intuitionistic fuzzy logic, which also accounts for uncertainty [7].

These methods helped in complex situations, like evaluating education programs, but they have limits. They assume all values stay between 0 (completely false) and 1 (completely true). In reality, performance can go beyond these limits. For example, a school might do much better than expected (above 1) or cause harm, like wasting money or giving false reports (below 0) [8].

To address this, Smarandache developed neutrosophic logic, which splits information into three parts Truth (T), Indeterminacy (I) and Falsehood (F) [9].

This was later expanded to neutrosophic offsets, which allow values to go beyond the [0, 1] range [10]. This helps model extreme cases, like overachievement or negative impacts.

The uncertain Set was extended by Smarandache [10] to uncertain OverSet (when some component is > 1), since he observed that, for example, an employee working overtime deserves a degree of membership > 1, with respect to an employee that only works regular full-time and whose degree of membership = 1; also to uncertain UnderSet (when some uncertain component is < 0), since, for example, an employee making more damage than benefit to his company deserves a degree of membership < 0, with respect to an employee that produces benefit to the company and has the degree of membership > 0; and in general to uncertain OffSet (when some uncertain components are off the interval [0, 1], i.e. some uncertain component > 1 and some uncertain component < 0).

Then, similarly, he extended them to the uncertain Logic/Measure/Probability/Statistics etc. were extended to respectively uncertain Over-/Under-/Off- Logic / Measure / Probability / Statistics etc.

By "uncertain" he meant all types of fuzzy and fuzzy-extensions (intuitionistic fuzzy, neutrosophic, spherical fuzzy, plithogenic, etc.).

Another key idea is Upside-Down Logic, which deals with situations where information is reversed, such as when a bad result is made to look good. This often happens in politics, media, or school reports when people want to hide problems or exaggerate success [11].

In 2024 Smarandache introduced the Upside-Down Logics, that consist in 'Falsification of the Truth' & 'Truthification of the False':

"about funny science, recreational mathematics, upside-down thinking, or contradictory reasoning (to think backward). Since a statement in some conditions may be true, in other conditions false, and a third type of conditions partially true and partially false (or indeterminate).

[...] Falsification of the Truth (when a true statement is transformed into a false one),

and the second one is the opposite: Truthification of the False (when a false statement is transformed into a true one)...

All transformations from <A> to <antiA> or vice versa are real

...Falsification and Truthification are mostly used in the Social

Sciences (Anthropology, Archaeology, Economics, Geography, History, Law, Linguistics, Politics, Psychology,Sociology), Philosophy, etc. excelling in Politics:

Falsifying the Truth of Enemies:

[...] seeking to diminish the enemy's positive side to the point of cancellation and to increase the enemy's negative side to the point of exaggeration;

and Truthifying the False of the Friends:

[... seeking to decrease the friend's negative side to the point of cancellation, and to increase the friend's positive side to the point of exaggeration.]"

Finally, N-norms and N-conorms, introduced by Smarandache, are tools to combine different performance scores, even when the data is uncertain or contradictory [12]. These helps create an overall score from multiple sources.

In short, past research has made progress in handling uncertainty, but we still need a model that:

a) Allows values beyond the [0, 1] range
b) Deals with misinformation or distorted data
c) Combines multiple uncertain sources into one score

This paper fills that gap by combining these tools into a practical model for education performance [5].

3. Methodology

This section explains how our new model, ON-UAM (Offset-Neutrosophic Upside-Down Assessment Model), works step by step. The goal is to measure how well basic education informatization is performing even when the data may be unclear, exaggerated, or misleading.

3.1 Modeling Performance with Neutrosophic Offsets

Most scoring systems use numbers between 0 and 1. For example, a score of 0 means complete failure, and 1 means perfect success. But what if a school does more than expected, or causes damage instead of improvement?

In our model, we allow scores to go above 1 (called overperformance) or below 0 (called underperformance). This creates a more realistic way to describe performance.

Each performance item (like digital access, teacher training, or student usage) is represented as:

$$x = (T, I, F)$$

Where:

T (Truth): How much the report is likely to be true.

I (Indeterminacy): How uncertain or unclear the data is.

F (Falsehood): How much the report might be false.

We allow values like:

$$T, I, F \in [\Psi, \Omega], \text{ where } \Psi < 0 \text{ and } \Omega > 1$$

Example:

A school reports it has very strong digital tools, but audits show some tools were unused. We may represent it as:

$$x = (1.2, 0.3, 0.4)$$

This means it claims high performance ($T = 1.2$), but we have doubts ($I = 0.3$), and some falsehood exists ($F = 0.4$).

3.2 Detecting Misleading Data with Upside-Down Logic

Sometimes, schools or officials may present incorrect data on purpose. For example:

a) They hide negative results (falsification of the truth).
b) They exaggerate positive outcomes (truthification of the false).

To detect this, we apply Upside-Down Logic, which flips the values. If a reported value is:

$$x^{(r)} = (T_r, I_r, F_r)$$

Then the upside-down version is:

$$x^{(u)} = (F_r, 1 - I_r, T_r)$$

This transformation helps us model how data might be twisted in reports. It's useful when checking reports from different sources (e.g., government vs. teachers).

3.3 Combining Indicators Using N -norms and N -conorms

Performance is usually based on many indicators:

a) Technology access
b) Internet usage
c) Teacher training
d) Software availability

Each of these can be modeled as a neutrosophic score, like:

$$x_1 = (T_1, I_1, F_1), x_2 = (T_2, I_2, F_2), \ldots, x_n = (T_n, I_n, F_n)$$

We use N-norms to combine them (for strict logic) and N-conorms (for flexible logic).

N-norm (AND-like logic):

$$Nn(x_i, x_j) = \left(T_i \cdot T_j, \max(I_i, I_j), \max(F_i, F_j)\right)$$

N -conorm (OR-like logic):

$$Nc(x_i, x_j) = \left(T_i + T_j - T_i \cdot T_j, \min(I_i, I_j), \min(F_i, F_j)\right)$$

These formulas help us merge scores into one unified view, even if they include uncertainty or errors.

3.4 Final Informatization Score

To create a simple number that shows how well a school is doing overall, we define:

$$PIS = \alpha \cdot T + \beta \cdot (1 - F) - \gamma \cdot I$$

Where:

a) T = total truth score
b) F = total falsehood score
c) I = total indeterminacy (uncertainty)
d) α, β, γ = weights to adjust importance (e.g., $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$)

This formula gives a clear score between good and bad, while including how much we trust the data.

3.5 Example: A School Evaluation

Suppose a school reports three informatization indicators:

Indicator	T	I	F
Digital devices	1.2	0.2	0.3
Internet access	0.8	0.4	0.2
Teacher ICT training	0.5	0.5	0.6

We use the N -norm to combine them:

Step 1: Combine first two indicators:

$$Nn_1 = (1.2 \cdot 0.8, \max(0.2,0.4), \max(0.3,0.2)) = (0.96,0.4,0.3)$$

Step 2: Combine result with third indicator:

$$Nn_2 = (0.96 \cdot 0.5, \max(0.4,0.5), \max(0.3,0.6)) = (0.48,0.5,0.6)$$

Step 3: Compute final score using $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$:

$$PIS = 0.5 \cdot 0.48 + 0.3 \cdot (1 - 0.6) - 0.2 \cdot 0.5 = 0.24 + 0.12 - 0.1 = 0.26$$

The school's informatization performance is weak (score = 0.26 out of 1), and the high falsehood and uncertainty lower the final result. Despite reporting high device numbers, teacher training and data trust are low.

4. Mathematical Equations

This section explains the mathematical foundation of the ON-UAM model. We define equations, explain each part, and provide full numerical examples step-by-step. The goal is to help readers understand how the model works in real evaluations of education informatization.

4.1 Neutrosophic Representation of Performance

Every performance indicator is represented by a Neutrosophic Offset Vector:

$$x = (T, I, F)$$

Where:

T : truth value, possibly > 1 (overperformance)

I : indeterminacy value, showing uncertainty

F : falsehood value, possibly < 0 (negative effect)

These values are allowed to lie in an extended range:

$$T, I, F \in [\Psi, \Omega] \text{ where } \Psi < 0, \Omega > 1$$

4.2 Upside-Down Transformation Equation

We define the Upside-Down Logic Transformation (UDLT) as:

$$UDLT(x) = (F, 1 - I, T)$$

This means:

a) Truth becomes Falsehood

b) Indeterminacy is inverted (high uncertainty becomes low trust)

c) Falsehood becomes Truth

Example:

If a report gives:

$$x = (1.1, 0.3, 0.2)$$

Then:

$$\text{UDLT}(x) = (0.2, 0.7, 1.1)$$

This transformation is used when we suspect the data is biased or politically influenced.

4.3 Aggregation Equations Using N-Norm and N-Conorm

We use N -norm and N -conorm to combine different indicators.

N -norm (intersection):

$$Nn(x_1, x_2) = \left(T_1 \cdot T_2, \max(I_1, I_2), \max(F_1, F_2)\right)$$

N -conorm (union):

$$Nc(x_1, x_2) = \left(T_1 + T_2 - T_1 \cdot T_2, \min(I_1, I_2), \min(F_1, F_2)\right)$$

These operators allow us to combine scores with attention to both uncertainty and distortion.

4.4 Final Informatization Score (PIS) Equation

To compute one single score that shows overall informatization performance, we use:

$$PIS = \alpha \cdot T + \beta \cdot (1 - F) - \gamma \cdot I$$

Where:

T : combined truth value from all indicators

F : combined falsehood value

I: combined indeterminacy

α, β, γ : weights (must add up to 1)

Note:

a) $1 - F$ reflects how little falsehood exists (we want less).

b) The lower the indeterminacy (I), the higher the trust in the result.

4.5 Full Numerical Example

Let's assume a school has the following three indicators:

Indicator	T	I	F
Internet Access	1.1	0.3	0.1
Teacher ICT Training	0.9	0.4	0.2

E-learning Platform Usage	0.6	0.5	0.3

We compute step by step using N -norm.

Step 1: Combine Indicator 1 & 2

$$Nn_1 = (1.1 \cdot 0.9, \max(0.3,0.4), \max(0.1,0.2)) = (0.99,0.4,0.2)$$

Step 2: Combine result with Indicator 3

$$Nn_2 = (0.99 \cdot 0.6, \max(0.4,0.5), \max(0.2,0.3)) = (0.594,0.5,0.3)$$

Step 3: Compute PIS using weights $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$

$$PIS = 0.5 \cdot 0.594 + 0.3 \cdot (1 - 0.3) - 0.2 \cdot 0.5$$

$$PIS = 0.297 + 0.21 - 0.1 = 0.407$$

This school's informatization performance score is 0.407 out of 1. The high truth value helped, but uncertainty (I = 0.5) and moderate falsehood (F = 0.3) reduced the overall result.

5. Results & Analysis

In this section, we show how the ON-UAM model works in practice. We apply it to real-life-like data and explain what the results mean. We use the mathematical formulas from the previous section and present the results in clear tables.

5.1 Scenario

Imagine we are evaluating three different schools (School A, B, and C). Each school reports its performance in three areas of education informatization:

1. Access to digital tools
2. Teacher training in technology
3. Use of digital learning platforms

Each of these areas is rated using neutrosophic values — including truth (T), indeterminacy (I), and falsehood (F). The values may go above 1 (overperformance) or below 0 (harmful performance).

Collected Data below:

School	Area	T	I	F
A	Digital Access	1.2	0.2	0.1
	Teacher ICT Training	1.1	0.3	0.2
	Digital Learning Usage	0.9	0.4	0.3
B	Digital Access	0.7	0.5	0.3
	Teacher ICT Training	0.6	0.6	0.4
	Digital Learning Usage	0.5	0.4	0.5
C	Digital Access	1.3	0.1	0.1
	Teacher ICT Training	1.0	0.2	0.1

Digital Learning Usage	1.1	0.1	0.2

Calculations for Each School

Let's apply the N-norm for each school and compute the final PIS (Performance Informatization Score) using weights: $\alpha = 0.5, \beta = 0.3, \gamma = 0.2$

School A

Step 1: Combine first two indicators

$$Nn_1 = (1.2 \cdot 1.1, \max(0.2,0.3), \max(0.1,0.2)) = (1.32,0.3,0.2)$$

Step 2: Add third indicator

$$Nn_2 = (1.32 \cdot 0.9, \max(0.3,0.4), \max(0.2,0.3)) = (1.188,0.4,0.3)$$

Final Score (PIS):

$$PIS = 0.5 \cdot 1.188 + 0.3 \cdot (1 - 0.3) - 0.2 \cdot 0.4$$
$$PIS = 0.594 + 0.21 - 0.08 = 0.724$$

School B

Step 1:

$$Nn_1 = (0.7 \cdot 0.6, \max(0.5,0.6), \max(0.3,0.4)) = (0.42,0.6,0.4)$$

Step 2:

$$Nn_2 = (0.42 \cdot 0.5, \max(0.6,0.4), \max(0.4,0.5)) = (0.21,0.6,0.5)$$

Final Score:

$$PIS = 0.5 \cdot 0.21 + 0.3 \cdot (1 - 0.5) - 0.2 \cdot 0.6 = 0.105 + 0.15 - 0.12 = 0.135$$

School C

Step 1:

$$Nn_1 = (1.3 \cdot 1.0, \max(0.1,0.2), \max(0.1,0.1)) = (1.3,0.2,0.1)$$

Step 2:

$$Nn_2 = (1.3 \cdot 1.1, \max(0.2,0.1), \max(0.1,0.2)) = (1.43,0.2,0.2)$$

Final Score:

$$PIS = 0.5 \cdot 1.43 + 0.3 \cdot (1 - 0.2) - 0.2 \cdot 0.2 = 0.715 + 0.24 - 0.04 = 0.915$$

Summary of Results

School	Combined T	Combined I	Combined F	PIS Score
A	1.188	0.4	0.3	0.724
B	0.21	0.6	0.5	0.135
C	1.43	0.2	0.2	0.915

Then:

a) School C had the highest score (0.915), showing strong informatization and reliable data.
b) School A performed well (0.724), but had higher uncertainty and some possible exaggeration.
c) School B had a low score (0.135) due to weak performance and high indeterminacy and falsehood.

This shows that ON-UAM can clearly identify not only how good a school is doing, but also how reliable and honest their data appears to be.

6. Discussion

The results in the previous section show how the ON-UAM model gives us a deeper and more realistic understanding of performance in basic education informatization. This section explains what the findings mean and why this model is important.

6.1 Recognizing More Than Just Numbers

Traditional evaluation systems only look at how high or low a score is. But they do not consider whether the score is honest, exaggerated, uncertain, or incomplete. With ON-UAM, we are not just looking at what is reported, we are also looking at how reliable and balanced that report is.

For example, School A reported strong performance, but it had some uncertainty and falsehood in the data. ON-UAM showed this by lowering the final score based on those hidden issues. In contrast, School C had very strong performance and highly trustworthy data. The model rewarded that with a higher score.

This is an important improvement because in real-world settings, some schools or systems might:

a) Report better results than reality (e.g. due to funding pressure or politics),
b) Be unsure of their data (e.g. lack of audits),
c) Or truly perform at very high or very low levels.

ON-UAM can capture all of these cases.

6.2 Realistic Score Ranges: Above 1 and Below 0

In our model, performance values can go beyond the traditional 0 to 1 range. This allows us to represent:

a) Overperformance: When a school does more than expected (e.g. 130% success → $T = 1.3$)
b) Underperformance or harm: When a school not only fails but also causes problems (e.g. a T value < 0)

This feature helps the education systems be more honest in tracking both improvements and failures.

6.3 Value of Upside-Down Logic

One of the most innovative parts of the model is the use of Upside-Down Logic. This transformation helps reveal whether reported data may have been "spun" or altered especially in environments where politics or media influence education reporting.

For example:

a) If a report says a program is 100% successful (T = 1), but field feedback shows it was never used (F = 1), the UDLT transformation will reveal this mismatch.
b) This feature can be used in audits or reviews to test the honesty of performance claims.

6.4 Flexible and Fair Aggregation

Using N-norms and N-conorms, our model combines multiple indicators (like access, training, usage) in a way that is flexible:

a) If one area is weak but others are strong, the model adjusts fairly.
b) If all areas are strong and reliable, the final score is higher.

This prevents schools from hiding poor performance in one area behind high scores in another. It also handles cases where data might be missing or unclear.

6.5 Broader Use and Future Application

Even though this paper focuses on basic education informatization, the ON-UAM model can be used in other fields too, such as:

a) Evaluating government performance
b) Checking the success of health programs
c) Auditing large-scale technology projects

It can also be extended in the future to include time-based changes, team-based reporting, or automated decision systems.

7. Conclusion

In this paper, we created a new model called ON-UAM to measure how well schools are using technology in education. This model is different because it does not just look at numbers   it also checks if the numbers are true, unclear, or possibly wrong.

We used three smart ideas:

a) Neutrosophic Offsets: to allow performance to be better than normal (above 1) or worse (below 0),
b) N-norms: to combine many indicators like internet, teacher training, and digital tools,
c) Upside-Down Logic: to find if the data was changed or made to look better than it is.

With this model, we can give fair scores to schools. If a school performs well and gives honest data, it gets a high score. If a school gives weak or false data, its score will be lower. We also showed how this model works using clear steps, examples, and real formulas. It can help schools, governments, and education experts see the true picture even when information is uncertain or mixed. This model is not just for education. It can also help in other fields like health, business, or government, where performance is important and honesty matters. ON-UAM is a useful, flexible, and fair tool for measuring performance in the real world.

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