Discovery of Potential High Utility Itemset from Uncertain Database using Multi Objective Particle Swarm Optimization Algorithm

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***Abstract*—In recent decades, Internet of Things devices have grown in popularity across a wide range of industries and uses. As a result, vast amounts of data are created and generated. Despite the fact that the collected data contains a great quantity of crucial information, most current and general pattern mining algorithms simply analyses a single item and exact information to identify the needed data. Because the amount of data gathered is so huge, it is vital to identify meaningful and updated data in a short period of time. In this paper, we use a multi-objective evolutionary framework to effectively mine the interesting Potential High Utility Itemset (PHUI) in a limited period, with the majority of items being PHUI utility and uncertainty. In an unpredictable context, the benefits of the proposed model (dubbed MOPSO-PHUIM) can identify lucrative PHUIs without pre-defined threshold values (i.e., minimal utility and minimum uncertainty). To illustrate the efficiency of the created MOPSO-PHUIM, two encoding techniques are also taken into account. Using the developed MOPSO-PHUIM model for decision-making, a set of non-dominated PHUIs may be found in a short amount of time. Studies are then carried out to demonstrate the utility and performance of the built MOPSO-PHUIM model in terms of velocity, hyper volume, and the different result discovered when compared to generic techniques.**

Keywords—High Utility Itemset; Evolutionary Computation; Particle Swarm Optimization; Multi Objective; Uncertainty;

I. Introduction

First, a Multi Objective Particle Swarm Optimization Algorithm to Mine Potential High Utility Itemset Mining (MOPSO-PHUIM) model is created, which can be utilised to identify the needed PHUIs in a finite amount of time in an uncertain environment . The created MOPSO-PHUIM does not require previous information for knowledge discovery, such as a minimum utility threshold or a minimum uncertainty threshold, but instead mines non-dominated patterns, which are undeniably more one of a kind and helpful for navigation and decision making [1]. The Tchebycheff approach which is based on the weight is used to produce uncontrolled solutions fast using a multi-objective framework (help and uncertainty). In terms of mixing, high volume, and a number of known patterns, tests have shown that the proposed MOPSO-PHUIM exceeds the standard drilling algorithms [2].

Uncertainty refers to epistemic situations in which information is incomplete or unknown. It can be used to future event forecasts, existing physical data, or the unknown. Uncertainty can emerge in partially visible or stochastic contexts, as well as through ignorance, indolence, or a combination of the two. Insurance, philosophy, physics, statistics, economics, finance, medicine, psychology, sociology, engineering, metrology, meteorology, ecology, and information science are just a few examples[3] [4].

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II. RELATED WORKS

A. High Utility Itemset Mining

To circumvent the FIM downside, a method known as high-utility itemset mining (HUIM) is used on the any given transaction dataset to identify the itemset in good utility in the dataset. The policy behind HUIM is that, mined itemset will have utility value greater than the threshold utility determined by the user [5]. The support (or frequency) of an itemset is anti-monotonic in the FIM issue, for example. With this capability, you can successfully narrow down the search space. Various pursuit methodologies, structure development strategies, information portrayal techniques, and pruning techniques, including a progression of algorithms dependent on level-wise competitor age and testing, algorithms dependent on pattern or tree development, and also utility centered algorithms, have been proposed to mine HUIs all the more sensibly and successfully [6]. However, the size of solution search space increases rapidly as the diversity of items and transaction count increases in the dataset. High-utility itemset mining (HUIM) is a new study topic that looks at both item unit profit and quantity to extract a collection of high data items (HUIs) from quantitative datasets. HUIM's purpose is to discover similarities that are incredibly valuable to users. A HUI is defined as an object or collection whose utility exceeds a predefined minimum utility threshold. Using the HUIM, more profitable goods or partnerships may therefore be found, This information may then be utilised to create more efficient decision-making systems [7]. Besides, most current pattern mining approaches depend on a deduced threshold worth to distinguish the necessary data, which is a troublesome cycle in light of the fact that deciding a suitable threshold to stay away from issues like "uniqueness" and "combinatorial and exponential blast" requires area and master information. Evolutionary computing is a powerful stochastic optimization method that is inspired by nature's evolutionary process and uses natural evolution principles to find the best solution. Traveling salesman problem, data mining, work shop scheduling problem, unit commitment challenges, disassembly sequence planning, feature selection, and other combinatorial optimization problems have all been solved using EC. EC-based techniques such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and the artificial bee colony algorithm have been presented to explore the vast search area of HUIM. EC-based HUIM algorithms, on the other hand, usually take a long time to generate the HUIs which meet the minimal utility requirement. This topic may be broken down into two components, both of which can be summarised. Because EC-based techniques frequently seek the good solution from the past generation, certain HUIs may be omitted during the evolutionary process [8]. But to have efficient methodology, all items which satisfying the threshold value of utility should be mined by HUIM; EC-based methodologies frequently look for the best qualities from the past age, which might disregard specific HUIs in the transformative interaction. With regards to finding new HUIs, HUIM algorithms working based on EC are ineffective .

B. High Utility Itemset mining from Uncertain database

The data sources are assumed to be exact in most utility-based techniques, and the data uncertainty component is ignored. Without the unknown element, the calculated trends may become meaningless, untrustworthy, and lacking of critical data, with a poor chance of success. Data faces several problems in a complex industrial context, including uncertainty regarding data sources and processing environment elements. Because many resources have an element of uncertainty. Traditional data mining methodologies are incapable of extracting all of the relevant information from ambiguous datasets [9]. This is because of the way that the two parts are particular measurements and are distinct that characterize the lexical and instinctive worth of any pattern [10]. To asses the significance of pattern in a given transaction dataset, utility measure is used by Normal information mining systems. The questionable level might be considered as an actual meter that actions the example's trustworthiness and presence as far as probability. It is vital to have a consistent system that analyses both unknown and value aspects at the same time in order to gather the facts needed to make an effective choice in a short amount of time.

C. Evolutionary approaches to solve High Utility Itemset Mining

We investigate the topic by using evolutionary computing by considering both uncertainty factor and utility factor on a uncertain dataset and identify the non-dominated itemset having potentially greater utility (PHUIs). Multi Objective Particle Swarm Optimization for Potential High Utility Itemset Mining (MOPSO-PHUIM) model is the first to be created, and it may be used to locate the needed PHUIs in a limited period in an unpredictable environment [11].
The developed MOPSO-PHUIM does not require previous information for knowledge discovery, such as a minimal utility threshold or a minimum uncertain threshold, but it may mine non-dominated patterns, which are considerably more distinctive and relevant for decision-making [12].

III. PRELIMINARY SETUP

In this section, we describe the MOPSO-PHUIM model, which is based on MOPSO, for generating non-dominated potentially high utility itemsets (PHUIs) from quantifiable and imprecise datasets.

A. MOPSO-PHUIM Algorithm

The developed MOPSO-PHUIM takes into account both utility and uncertainty aspects in order to find a collection of non-dominated potentially high utility itemset (PHUIs) from uncertain datasets. Both of these criteria are in some way at odds with one another pattern with greater utility often do not have higher uncertainty, while patterns with less utility sometimes don't result in increased value. It may be regarded of as a two-objective optimization problem since it evaluates those two factors together without prior knowledge. When compared to traditional pattern-mining algorithms, the

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suggested approach only reveals a few significant patterns that may be utilised to make judgments.

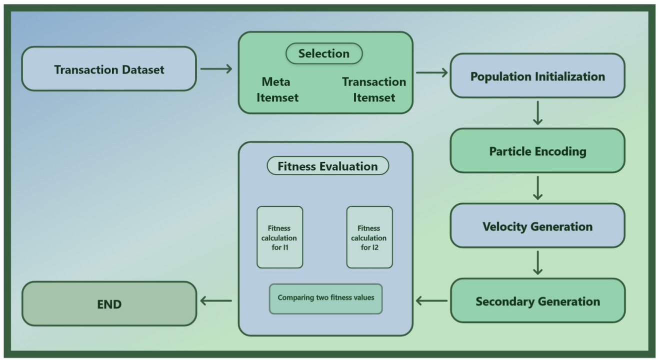

Fig. 1. MOPSO-PHUIM Workflow

B. *Initialization*

As the population may lead to a bad outcome or take a long time to converge, population initialization is a critical phase in the MOE technique. The sample dataset utilised in the study, represents three values such as item; quantity; uncertainty respectively. The profit for individual items are given separately in table .Using random item selection, the starting population was generated at random fetched by the databases. The arbitrary item selection strategy, on the other hand, always yields incorrect patterns. In other words, the pattern is missing from the transactions.

```
Algorithm 1 : Initialization :
INPUT  : The Transaction Dataset D , where T is the Transaction
         i is the item
OUTPUT : Initial selection I
Step 1 : for each T belongs to D do :
Step 2 : |      M   <-- (utility(i)) / total utility
Step 3 : end for
Step 4 : for each i belongs to D do :
Step 5 : |      T   <-- uncertainty(i) / total uncertainty
Step 6 : end for
Step 7 : M  <--  Ascending sort(M)
Step 8 : T  <--  Descending sort(T)
Step 9 : I  <--  [ 50%(M) , 50%(T) ]
```

Fig. 2. Algorithm 1: Initialization

A problem-specific beginning approach was described in the first phase of the developed MOPSO-PHUIM. Meta itemset selection and transaction itemset selection are the two methods we use to choose the population. Fig. 2. Illustrate the Initialization algorithm. The utility probability is used to choose the 50 percent of the population from the database transactions as shown in Algorithm 1 (steps 4 to 6). This technique ensures that the database's final solutions are all of the chosen items. Just one item from the transaction is encoded and picked based on uncertainty probability (meta itemset selection Algorithm) for the remaining 50% of items in a population 1 step 1 to 3.

C. *Encoding*

The particle swarm optimization approach is initiated in this phase by generating its population. The population is made up of pop size particles, each of which represents a database transaction. A particle can be formally defined as a vector V belonging to a dimension D. In a dataset, the count of unique item is represented by D. Fig.3. Illustrates the Encoding Algorithm. Table. 1. Show the encoded particles.

```
Algorithm 2 : Particle Encoding and Velocity Generation

INPUT  : Initial Selection I
OUTPUT : Particle Encoding (P) , Velocity Generation (V)

Step 1 : for each i ∊ I:
Step 2 : |      if i ∊ T , Pi <-- Encode(1)
Step 3 : |      if i does not ∊ T ,Pi <-- Encode(0)
Step 4 : end for
Step 5 : for each i ∊ I:
Step 6 : |      Generate Velocity(Vi) <-- Random()
Step 7 : end for
Step 8 : Initialize I2 , I2 <-- copy(I)
Step 9 : Update the Velocity(V2) for I2
```

Fig. 3. Algorithm 2: Enoding

TABLE I. ENCODED PARTICLES

Encoding transactions as particles.

	a	b	c	d	e
$\vec{p}_{(1)}$	1	1	0	1	1
$\vec{p}_{(2)}$	1	1	1	0	0
$\vec{p}_{(3)}$	0	0	1	1	1
$\vec{p}_{(4)}$	1	1	1	1	0
$\vec{p}_{(5)}$	0	0	0	1	1

D. *Velocity Appraise*

The velocity of each particle is arbitrarily generated during this phase. Fig.4. (Algorithm Step 5 to 7). Each particle is associated with velocity vector v of dimension d. d should satisfy the constraint that for all I consisting of T, $-v_{max}$ <= vi <= v_{max}. Table II below displays an example of particle velocities being initialized, where each particles p(i) velocity is represented by v(i). After initialization of the encoded particle's velocity, its fitness is assessed, as explained in the next section.
.

TABLE II. VELOCITY OF PARTICLES

Initializing particles' velocities.

	a	b	c	d	e
$\vec{v}_{(1)}$	0.343757	0.640539	0.636980	0.724399	0.719616
$\vec{v}_{(2)}$	0.521030	0.409739	0.092495	0.572762	0.503367
$\vec{v}_{(3)}$	0.838405	0.369433	0.644313	0.647657	0.709206
$\vec{v}_{(4)}$	0.336895	0.611416	0.768125	0.923636	0.409901
$\vec{v}_{(5)}$	0.359932	0.072850	0.858039	0.868211	0.133234

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```
Algorithm 3 : Secondary Generation :
INPUT   : Initial Selection Particle (P)
OUTPUT  : particle global best vector(p'(g));
          particle local best vector(p'(b))
Step 1  : P(b) ← Copy(P)
Step 2  : p'(g) ← FindBestParticle(P(b))
Step 3  : Compute balancing factor K by formula (3)
Step 4  : for i ← 1 to iterations do updating
Step 5  : |     for each (p',v,fit(p'))∈P,(p'(b),v(b),fit(p'(b)))∈P(b) do
Step 6  : |     |       Update velocity v  formula (2) and (3)
Step 7  : |     |       Update particle p' by formula (1)
Step 8  : |     |       Compute fitness of p': fit(p') by formula
Step 9  : |     |       if fit(p') > fit(p'(b)) then
Step 10 : |     |       |       p'(b) ← Copy(p')
Step 11 : |     |       |       p'(g) ← FindBestParticle(P(b))
Step 12 : |     |       end if
Step 13 : |     end for
Step 14 : end for
```

Fig. 4. MOPSO-PHUIM

A secondary particle is necessary to compare the fitness value to extract the high expected pattern . the secondary particle is given by the (1)

$$p_i(t+1) = \begin{cases} 1, & \text{if } r < S(v_i(t+1)) = \dfrac{1}{1+e^{-v_i(t+1)}} \\ 0, & \text{otherwise,} \end{cases} \quad (1)$$

Here v_i represents the updated velocity, t represents the transaction. The updated velocity v_i is previously calculated using the (2).

$$v_i(t+1) = k \cdot [v_i(t) + c_1 \cdot r_1 \cdot (p_{(b)i} - p_i(t)) + c_2 \cdot r_2 \cdot (p_{(g)i} - p_i(t))] \quad (2)$$

where k is the balancing factor, c1 and c2 are the individual factor and social factor respectively, r1 and r2 are the random values whose sum equals 1, t is the discrete time. The balancing factor can be given by the (3)

$$k = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4 \cdot \varphi}\right|}, \varphi = c_1 + c_2, \text{ and } \varphi \geq 4 \quad (3)$$

In the MOPSO-PHUIM, the Fitness Function is employed to find non-dominated outcomes based on utility and uncertainty components. Fig.5. show the fitness function algorithm and the formula to calculate the fitness is specified in the (4) below. It is used to evaluate the quality of the encoding scheme. Fitness function's goal is to provide an efficient set that aids in the discovery of non-dominated high anticipated utility patterns.

```
Algorithm 3 : Fitness Evaluation :

INPUT  : Initial Selection I,I2 ; Particle Encoding (P1),(P2);
         Generated Velocity (V1),(V2):
OUTPUT : Fitness Evaluation (F1),(F2):

Step 1 : Calculate Fitness for I1 , F1
Step 2 : Calculate Fitness for I2 , F2
Step 3 : for each i,j belongs to F1,F2
Step 4 : |      Compare F1i and F2j , Find fittest value , fij
Step 5 : |      MOPSO <-- Fittest Value , fij
Step 6 : end for
```

Fig. 5. Fitness Evaluation Equation

$$Z = \max[w1i * (ui - U), w2i * (unci - UNC)] \quad (4)$$

Here, w1 – Weight 1 of the individual particle i

w2 – Weight 2 of the individual particle i
ui – Utility of the individual particle i
U – Maximum utility of entire data set
unci – Uncertainty of individual particle
UNC – Maximum uncertainty of entire data set

The fitness function is computed for both I1 and I2. Then compare the fitness values F1 and F2 to obtain the fittest value fij, the resulting fittest value provides the non - dominated highly anticipated patterns.

IV. Experimental Evaluation

In this segment, we created the MOPSO-PHUIM model to two baseline methods, namely the U-Apriori algorithm, which needs a minimal uncertainty threshold, and the EFIM algorithm , which requires a minimum utility threshold. The experiment was deployed on a Windows 11 computer having an i5 9th Gen, Octa core processor and 16GB RAM.

A. Dataset Description

The Dataset consists of set of transactions. Each transaction consists of three parameters items , quantity and uncertainty. The Fig. 6. represents the sample dataset. The profit for individual items are separately defined in the profit table as shown in the Table III.

```
1 2 4 5 : 13 9 7 18 : 0.2 0.9 0.3 0.05
1 2 3 : 1 4 12 : 0.3 0.7 0.1
3 4 5 : 5 9 8 : 0.4 0.7 0.2
1 2 3 4 : 9 8 4 2 : 0.9 0.44 0.3 0.7
4 5 : 6 3 : 0.8 0.4
```

Fig. 6. Dataset containing Transactions, utility and uncertainity

TABLE III. ITEM PROFIT

ITEM	PROFIT
1	8
2	4
3	6
4	7
5	3

B. Environmental Description

Ten earlier calculations will be contrasted with the new methodology, HUIM-BPSO-nomut (BPSO-nomut for short). To start, it is differentiated to high-utility itemset mining procedures that do exclude however with not set in stone worth as a base utility standard TKU-(Top-K-Utility), TKO-(Top-K-Utility in) are two sorts of itemsets. The TKO is utilized all through the article. TKO Base, as given in the SPMF library, is utilized without streamlining. As an examination, the three calculations are employed, because they are customary calculations that don't need the client's feedback. Prior to starting the hunt, settle on a negligible utility basis is being

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completed K is the quantity of most elevated utility itemsets picked.

C. No of PHUIs Generated

If the number of potentially high utility itemset pattern generated is compared in accordance to minimum utility threshold and Tchebycheff value , then it is observed that the usage of Tchebycheff value has yielded more number of PHUI as compared to the minimum threshold method. Fig. 7. Shows the PHUIs generated by two methods

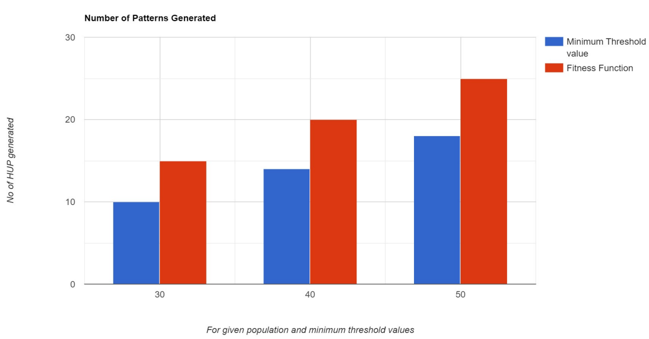

Fig. 7. No of PHUIs Generatede

D. Execution Time :

If the runtime of potentially high utility itemset pattern generated is compared in accordance to number of Transaction in the data set , then it is observed that using tchebycheff value results in lesser time as compared to minimum threshold method. Fig. 8. Show the execution time taken by the proposed algorithm.

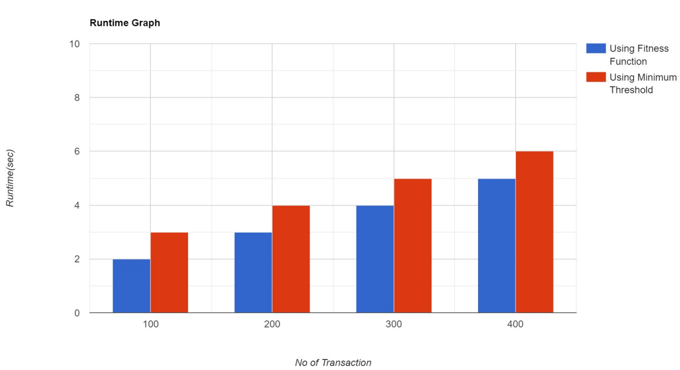

Fig. 8. Execution Time

Conclusion

Standard and wide affiliation rule mining, which has accumulated more consideration as of late, can yield more significant data than utility-design mining. Information vulnerability has turned into a genuine worry in the example mining space because of the quick development of innovation. Most of existing and nonexclusive methods, then again, involve building up a deduced edge for mining the necessary information, which is an intense methodology in many fields and regions. We incorporate the utility and vulnerability factors in this review and construct MOPSO-PHUIM, a development model dependent on MOPSO/D, to track down the non-overwhelmed Potentially High Utility Itemset (PHUIs). Two twofold and worth encoding blueprints are utilized to show the adequacy of the made MOPSO-PHUIM. Using the made MOPSO-PHUIM, it is effective to develop less yet usable non-ruled PHUIs for decision-production without deduced limit esteem in a capricious climate. In accordance with union, hyper volume, and the number of instances identified, studies are conducted to compare the quality and feasibility of the proposed framework to the general and traditional EFIM and U-Apriori models. Because the suggested multi-objective model can quickly use the two goals of usefulness and vulnerability in a suspect data collection, there are a plethora of other possibilities that might be investigated in a future study. In a multi-objective circumstance, for instance, when each tuple has its own likelihood dispersion, the method can deal with tuple vulnerability. More parts can be investigated for multi-objective circumstances to foster less however important non-overwhelmed designs. Broadening the proposed MOPSO-based method to the disciplines of dynamic information mining, top-k example mining and stream information mining are another interesting subject.

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