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Automation of USDA Triangle Soil Texture Classification Using Finite State Machine: A Novel Conceptual Modeling Approach

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Abstract

The USDA triangle is the most widely used model for soil texture classification. The problem with USDA triangle model was, it needs critical analysis for identification of soil textural class. To simplify the soil textural class prediction process the USDA triangle model was automated using finite state machine technique. The experimental results exhibited the equivalence between USDA triangle and automated soil textural classification model. The proposed automated model is efficient, reliable and user-friendly for prediction of soil textural class.

Key words: Clay fraction, Sand fraction, Silt fraction, Software model.

1. Introduction

Soil includes supplements, water, minerals and micro-organism, which gives living environment to all plants. Jha and Ahmad (2018). The dirt quality varies overtime due to changes in properties. Karlen *et al.* (2003), Ghosh *et al.* (2017), Doran *et al.* (1999), Rajan *et al.* (2016). The organic and physical property of soil has immense impact on fertility. Schoenholtz *et al.* (2000), Crittenden and de Goede (2016). Soil fertility is the ability to give supplements to the yield development. Peigne *et al.* (2017). The poor soil surface influences hydro coherent and biochemical procedures. Moncada *et al.* (2017). Soil properties variation has high effect on irrigation management. The dirt properties and land suitability are integral factor for structuring water system frameworks. Cho *et al.* (2016). Artificial Intelligence approaches are efficiently used for soil classification. Wu *et al.* (2018), Sirsat *et al.* (2017). The dirt texture has high impact on tillage practices, plant nutrients and liming application. Jovic *et al.* (2019). Modeling soil classes play crucial role in irrigation system water

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productivity. Zeng *et al.* (2016). The soil classification has long history, wherein the USDA triangle model is the widely used model worldwide. Hartermink (2015). The objective of the proposed study is automation of USDA triangle model. The finite state machine (FSM) approach is most widely used technique for automation of multidiscipline theoretical concepts. In the proposed model the USDA triangle model is automated and also retained the logical equivalence of manual approach over soil texture classification. In USDA triangle model, for many cases there are multiple transitions for a same sand, silt or clay fraction value, hence we have chosen non-deterministic finite state machine to design automated framework of USDA triangle soil texture classification.

2. Materials and Methods

The USDA triangle soil texture model and FSM concepts are integrated to design soil texture automation framework. An input string is passed to the model one character at a time, in which the model considers the current state and the new character and chooses the next state. In FSM model one of the states is designated as start state and consists of one or more final states. Final or accepting states are represented using double circle. In FSM model, if it runs out of the input and halts at final state then it accepts the input string otherwise, it rejects. The number of steps FSM executes is exactly equal to number of characters present in the string. The FSM has two variants, Non-Deterministic Finite State Machine (NDFSM) and Deterministic Finite State Machine (DFSM). In NDFSM, there will be multiple moves for one input symbol, the behavior is non-deterministic. In this section the USDA triangle model represented in Figure 1 is automated using NDFSM model. Groenendyk*et al.* (2015).

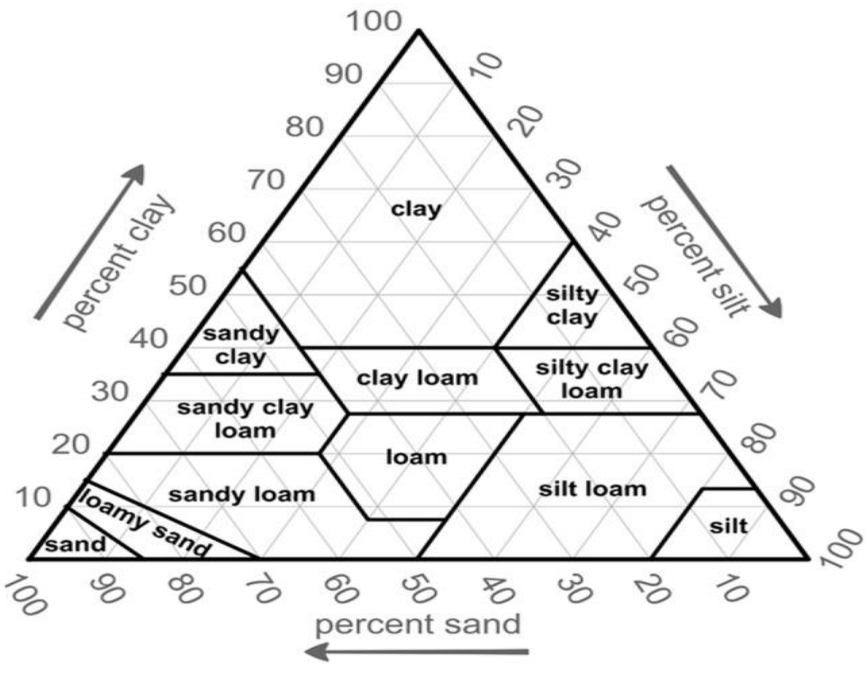

Figure 1: USDA triangle soil textural classification model

The sand, silt and clay fraction threshold values of twelve USDA triangle model classes are considered to identify the input parameters for NDFSM framework. The NDFSM model variables are defined in Table 1.

Table 1: Preprocessing of USDA triangle soil texture data to fit into NDFSM

Sand Fraction (%)	Sand Input Variables	Silt fraction (%)	Silt Input Variables	Clay fraction (%)	Clay Input Variables
0-20	$a1$	0-15	$b1$	0-7	$c1$
20-23	$a2$	15-20	$b2$	7-10	$c2$
23-42	$a3$	20-28	$b3$	10-12	$c3$
42-45	$a4$	28-30	$b4$	12-15	$c4$
45-50	$a5$	30-40	$b5$	15-20	$c5$
50-52	$a6$	40-50	$b6$	20-27	$c6$
52-65	$a7$	50-52	$b7$	27-35	$c7$
65-70	$a8$	52-60	$b8$	35-40	$c8$
70-80	$a9$	60-73	$b9$	40-55	$c9$
80-85	$a10$	73-80	$b10$	55-60	$c10$
85-90	$a11$	80-87	$b11$	60-100	$c11$
90-100	$a12$	87-100	$b12$	-	-

2.1.1. Design of automated model for soil texture classification using NDFSM

The NDFSM approach is one of easiest method of finite automata used for designing abstract machines. In the proposed model automated soil texture classification model is designed using NDFSM. NDFSM is formally defined as set of five attributes which are described in the following section for USDA triangle model.

NDFSM = $\{S, \Sigma, F, s0, \delta\}$

States (S): $\{s0, s1, s2, s3, s4, s5, s6, s7, s8, s9, s10, s11, s12, s13, s14, s15, s16, s17, s18, s19, s20, s21, s22, s23, s24, s25, s26, s27, s28, s29, s30, s31, s32, s33, s34\}$.

Start State is $s0$ and $\in S$.

A state is a circumstance of a framework relying upon past sources of info and causes a response on current information sources. States indicate the step by step procedure for soil textural class identification based on the sand, silt and clay fraction input. Suppose if sand fraction is 85-100%, silt fraction is 0-15% and clay fraction is 0-10% then in the FSM model state transitions takes place in the path $s0$->$s1$->$s2$->$s3$. The state $s0$ is the initial state, $s1$ and $s2$ are intermediate states and $s3$ is the final state, which represents sand soil textural class. Suppose if sand fraction is 70-90%, silt fraction is 0-30% and clay fraction is 0-15% then in the FSM model state transitions takes place in the path $s0$->$s4$->$s5$->$s6$. The state $s0$ is the initial state, $s4$ and $s5$ are intermediate states and $s6$ is the final state, which represents loamy sand textural class. Similarly for all the 12 soil texture classes there are different state transition paths based on the sand, silt and clay fraction values which are represented in Figure 2.

Input Alphabets (Σ): $\{a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, a11, a12, b1, b2, b3, b4, b5, b6, b7, b8, b9, b10, b11, b12, c1, c2, c3, c4, c5, c6, c7, c8, c9, c10, c11\}$. The sand fraction values are represented using the template "*ai*", in which the symbol '*a*' represents the sand fraction and '*i*' represents the parameter number. The parameter number is assigned based on the sand fraction threshold values of USDA triangle model soil textural classes. Suppose if sand fraction value is 0-20% then the corresponding input parameter is mapped as "$a1$". Suppose if sand fraction value is 20-23% then the corresponding input parameter is mapped as "$a2$". Likewise, for all the unique sand fraction range the input parameters are assigned, which are reported in Table 1.

The silt fraction values are represented using the template "bi", in which the symbol 'b' represents the silt and 'i' represents the parameter number. The parameter number is assigned based on the silt fraction threshold values of USDA triangle model soil textural classes. Suppose if silt fraction value is 0-15% then the corresponding input parameter is mapped as "$b1$". Suppose if silt fraction value is 15-20% then the corresponding input parameter is mapped as "$b2$". Likewise, for all the unique silt fraction range the input parameters are assigned, which are reported in Table 1.

The clay fraction values are represented using the template "ci", in which the symbol 'c' represents the clay and 'i' represents the parameter number. The parameter number is assigned based on the clay fraction threshold values of USDA triangle model soil textural classes. Suppose if clay fraction value is 0-7% then the corresponding input parameter is mapped as "$c1$". Suppose if clay fraction value is 7-10% then the corresponding input parameter is mapped as "$c2$". Likewise, for all the unique clay fraction range the input parameters are assigned, which are reported in Table 1.

Final States (F): $\{s3, s6, s9, s12, s15, s18, s21, s24, s26, s29, s31, s34\}$

In USDA triangle model there are 12 soil texture classes accordingly in FSM model 12 final states are defined. Each final state represents a soil texture class. The state "$s3$" represents sand class, "$s6$" represents loamy sand class, "$s9$" represents sandy loam, "$s12$" represents loam, "$s15$" represents silty loam, "$s18$" represents silt, "$s21$" represents sandy clay loam, "$s24$" represents clay loam, "$s26$" represents silty clay loam, "$s29$" represents sandy clay, "$s31$" represents silty clay and "$s34$" represents clay soil texture. For all valid input patterns the FSM model halts at one of the final state based on sand, silt and clay fraction values.

Transition functions (δ): It maps from S (state) $\times$ Σ (Input symbol) = S (States), the outcome of transition function can have set of states in NDFSM}.In the following section the NDFSM model is designed for soil texture classification considering the transition functions represented in Table 2.

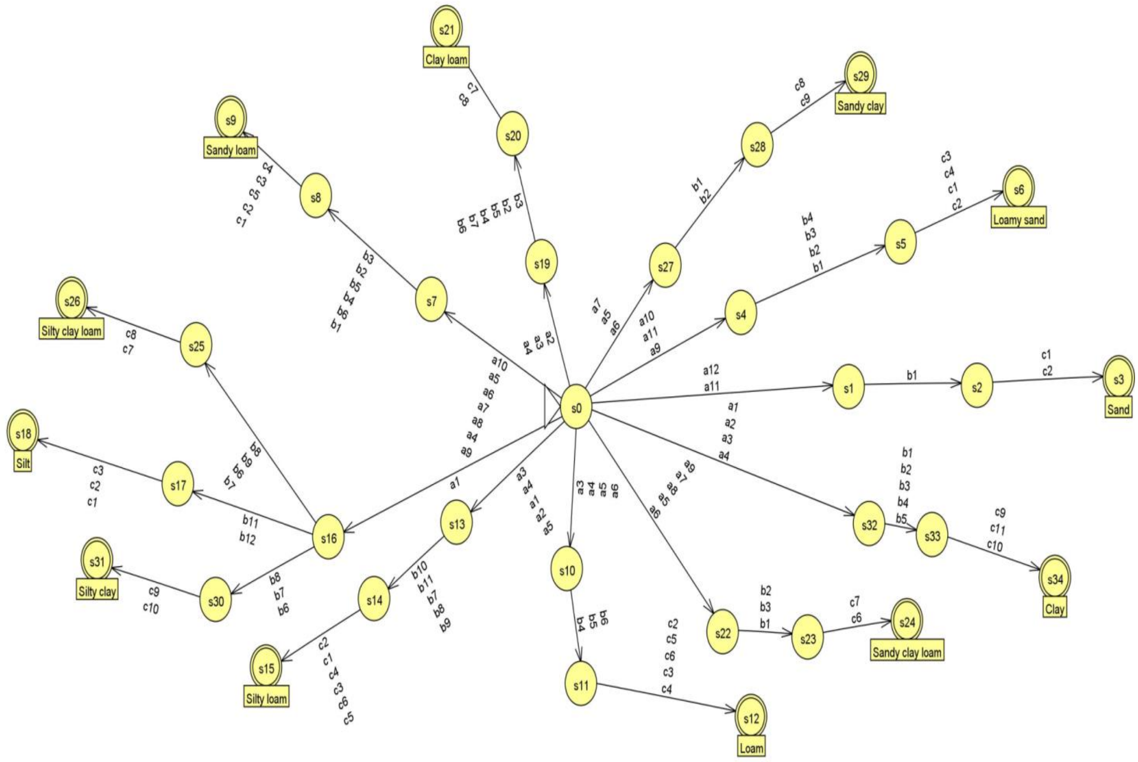

Figure 2: USDA triangle automated model for soil textural classification

Transition functions of proposed NDFSM model are highlighted in the following section over all the input symbols. For each state the possible movements on all the input parameters are represented using transition function. Suppose if the input comprises of sand fraction 91% then form start state *s*0 on input "*a*12" FSM moves to state "*s*1", followed by suppose if silt fraction is 5% then from state *s*1 on input "*b*1" FSM moves to state "*s*2" and followed by suppose if clay fraction is 6% then from state "*s*2" on input "*c*1" FSM moves to state "*s*3" and the corresponding input pattern is accepted as sand soil texture class.

Table 2: Transition functions defined for automated soil texture classification

Transition functions for states *s*0,*s*1,*s*2,*s*4,*s*5,*s*6,*s*7	Transition functions for states *s*8,*s*10,*s*11,*s*13,*s*14	Transition functions for states *s*16,*s*17,*s*19,*s*20,*s*22	Transition functions for states *s*23,*s*25,*s*27,*s*28, *s*30,*s*31,*s*32,*s*33
Transitions from state *s*0: *(s0, a1) = (s13, s16, s32)* *(s0, a2) = (s13, s19, s32)* *(s0, a3) = (s10, s13, s19, s32)* *(s0, a4) = (s7, s10, s13, s19, s32)* *(s0, a5) = (s7, s10, s13, s22, s27)* *(s0, a6) = (s7, s10, s22, s27)* *(s0, a7) = (s7, s22, s27)* *(s0, a8) = (s7, s22)* *(s0, a9) = (s4, s7, s22)* *(s0, a10) = (s4, s7)*	Transitions from state *s*8: *(s8, c1) =* ***(s9)*** *(s8, c2) =* ***(s9)*** *(s8, c3) =* ***(s9)*** *(s8, c4) =* ***(s9)*** *(s8, c5) =* ***(s9)*** Transitions from state *s*10: *(s10, b4) = (s11)* *(s10, b5) = (s11)* *(s10, b6) = (s11)* Transitions from	Transitions from state *s*16: *(s16, b11) = (s17)* *(s16, b12) = (s17)* *(s16, b6) = (s25)* *(s16, b7) = (s25)* *(s16, b8) = (s25)* *(s16, b9) = (s25)* *(s16, b6) = (s30)* *(s16, b7) = (s30)* *(s16, b8) = (s30)* Transitions from state *s*17:	Transitions from state *s*23: *(s23, c6) =* ***(s24)*** *(s23, c7) =* ***(s24)*** Transitions from state *s*25: *(s25, c7) =* ***(s26)*** *(s25, c8) =* ***(s26)*** Transitions from state *s*27: *(s27, b1) = (s28)* *(s27, b2) = (s28)* Transitions from

(s0, a11) = (s1,s4) (s0, a12) = (s1) Transitions from state s1: (s1, b1) = (s2) Transitions from state s2: (s2, c1) = **(s3)** (s2, c2) = **(s3)** Transitions from state s4: (s4, b1) = (s5) (s4, b2) = (s5) (s4, b3) = (s5) (s4, b4) = (s5) Transitions from state s5: (s5, c1) = **(s6)** (s5, c2) = **(s6)** (s5, c3) = **(s6)** (s5, c4) = **(s6)** Transitions from state s7: (s7, b1) = (s8) (s7, b2) = (s8) (s7, b3) = (s8) (s7, b4) = (s8) (s7, b5) = (s8) (s7, b6) = (s8)	state s11: (s11, c2) = **(s12)** (s11, c3) = **(s12)** (s11, c4) = **(s12)** (s11, c5) = **(s12)** (s11, c6) = **(s12)** Transitions from state s13: (s13, b7) = (s14) (s13, b8) = (s14) (s13, b9) = (s14) (s13, b10) = (s14) (s13, b11) = (s14) Transitions from state s14: (s14, c1) = **(s15)** (s14, c2) = **(s15)** (s14, c3) = **(s15)** (s14, c4) = **(s15)** (s14, c5) = **(s15)** (s14, c6) = **(s15)**	(s17, c1) = **(s18)** (s17, c2) = **(s18)** (s17, c3) = **(s18)** Transitions from state s19: (s19, b2) = (s20) (s19, b3) = (s20) (s19, b4) = (s20) (s19, b5) = (s20) (s19, b6) = (s20) (s19, b7) = (s20) Transitions from state s20: (s20, c7) = **(s21)** (s20, c8) = **(s21)** Transitions from state s22: (s22, b1) = (s23) (s22, b2) = (s23) (s22, b3) = (s23)	state s28: (s28, c8) = **(s29)** (s28, c9) = **(s29)** Transitions from state s30: (s30, c9) = **(s31)** (s30, c10) = **(s31)** Transitions from state s32: (s32, b1) = (s33) (s32, b2) = (s33) (s32, b3) = (s33) (s32, b4) = (s33) (s32, b5) = (s33) Transitions from state s33: (s33, c9) = **(s34)** (s33, c10) = **(s34)** (s33, c11) = **(s34)**

3. Results and Discussions

An analysis has been planned to scrutinize 12 classes in USDA soil textural triangle and its soil fraction ranges and developed a soft computing model to arrive at textural class. The objective of the proposed work is automation of USDA triangle soil texture classification concept using NDFSM. The data set comprises of 5000 records, in which each sample has sand, silt and clay particle size distribution. The summation of all three parameters particle size must be exactly 100 for all input samples. The 70% data was used for training, 20% data was used for testing and 10% data was used for validation. The testing and validation phase of experiment results exhibited the equivalence between USDA triangle model and FSM based automated software model. The model has been traced for many observed input patterns using JFALP. Rodger and Gramond (1998).The validation phase of the NDFSM soil texture classification model also obtained equivalence with USDA triangle over soil texture classification.

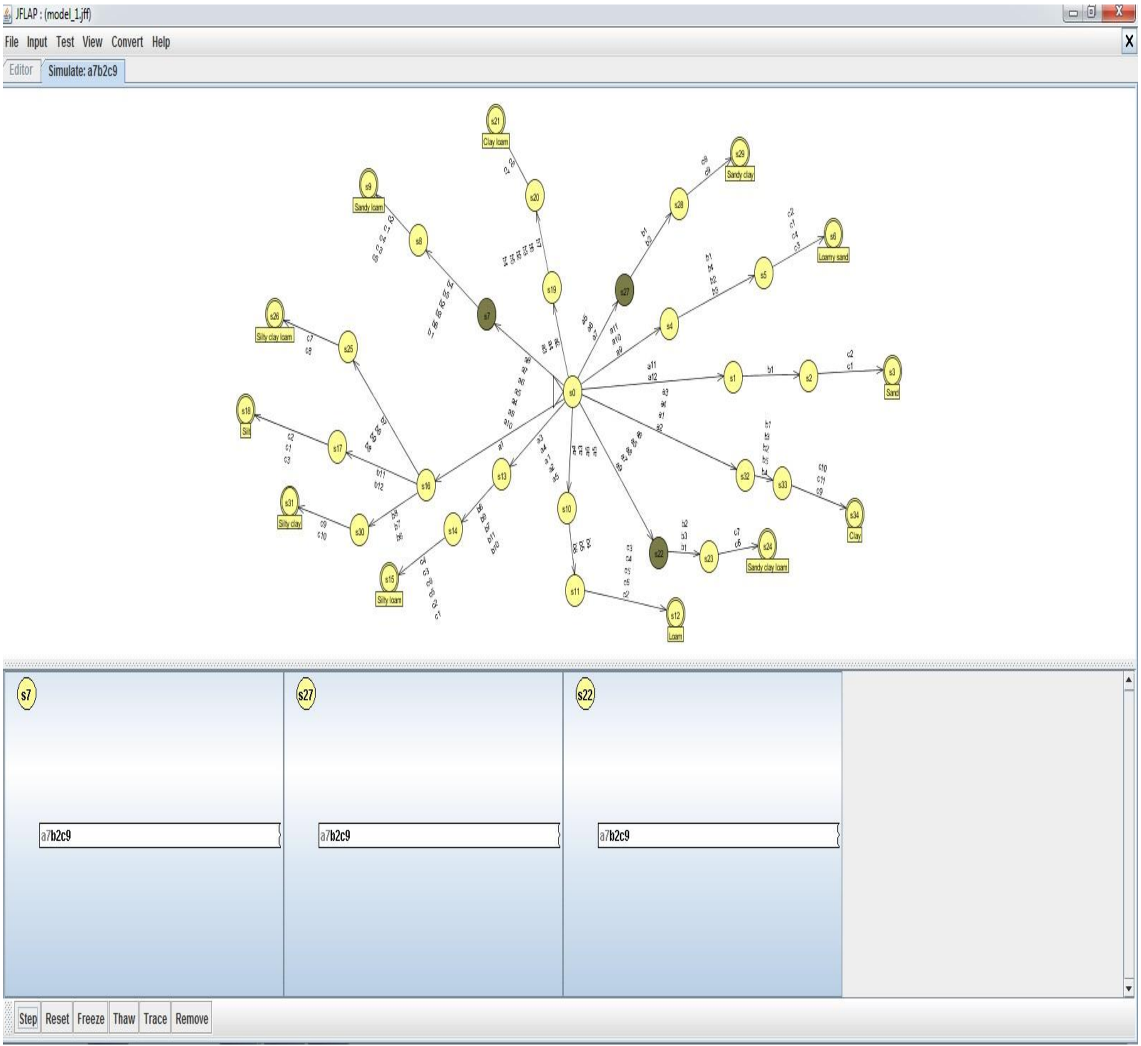

Figure 3: NDFSM model step by state tracing over the sand fraction value "*a*7"

The input pattern *"a*7*b*2*c*9*"* was traced using Java Formal Languages and Automata Package (JFLAP), in which the state transitions are observed over the sand fraction input *"a*7*"*. The transitions indicate the possible movements from state *s*0 over the input *"a*7*"* are *s*7, *s*22 and *s*27 which are highlighted in Figure 3.

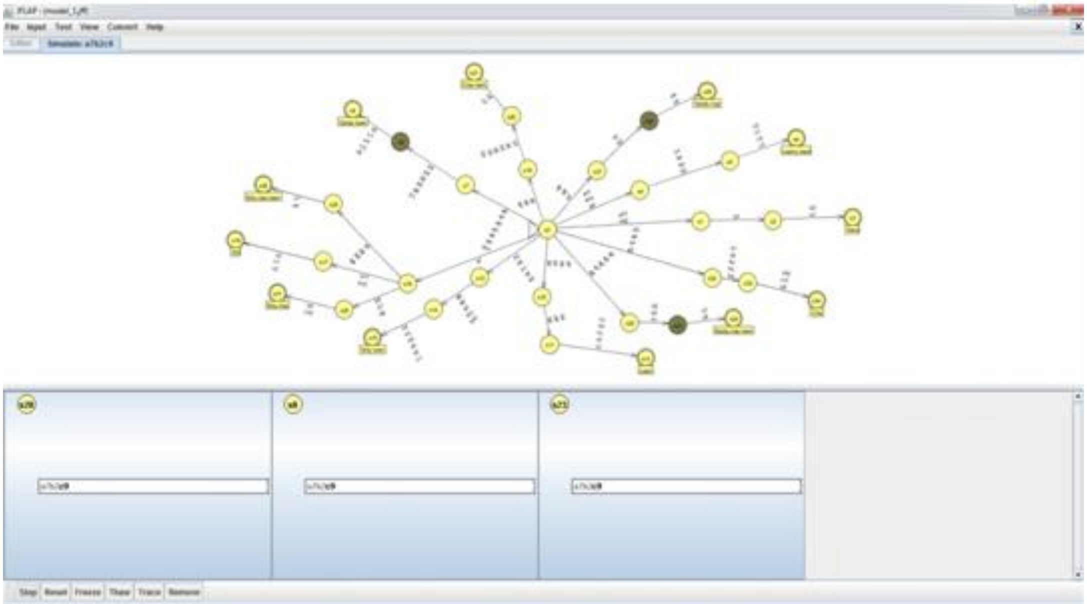

Figure 4: NDFSM model step by state tracing over the silt fraction input "*b*2"

The input pattern *"a*7*b*2*c*9*"* was traced using JFLAP, in which the state transitions are observed over sand fraction input *"a*7*"* followed by the silt fraction *"b*2*"*. The transitions indicate the possible movements over the input *"a*7*b*2*"* are *s8*, *s*23 and *s*28 which are highlighted in Figure 4.

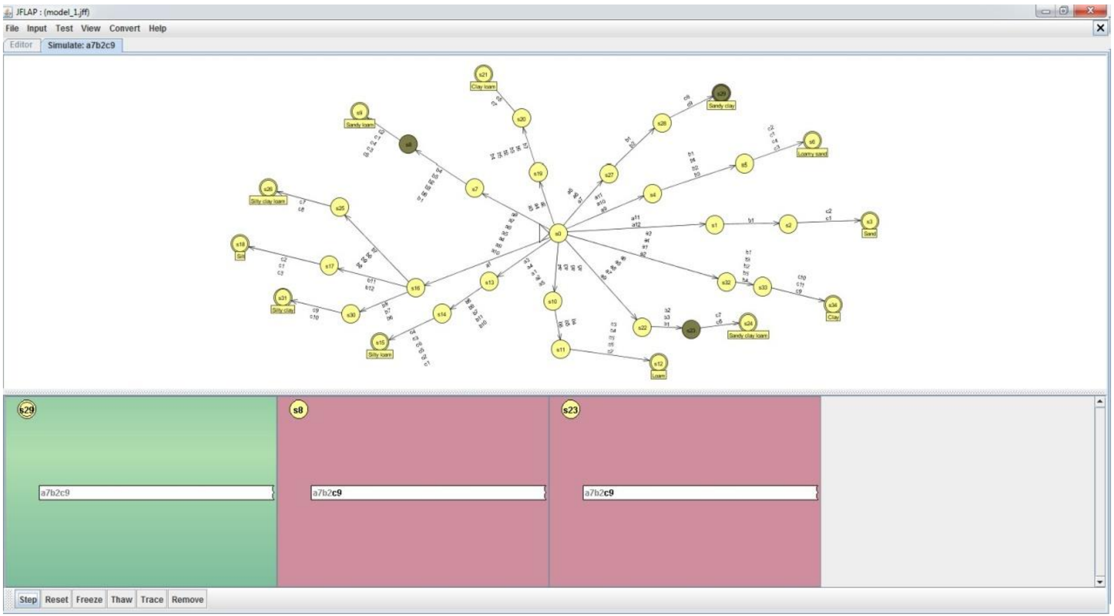

Figure 5: NDFSM model step by state tracing over the input symbol '*c*9'

The input pattern *"a*7*b*2*c*9*"* was traced using JFLAP, in which the state transitions are observed over sand fraction input *"a*7*"* followed by the silt fraction *"b*2*"*and followed by clay fraction *"c*9*"*. The transitions indicate the possible movements over the input *"a*7*b*2*c*9*"* are *s*29 which is final state highlighted in Figure 5 and represents sandy clay texture. Initially the execution starts from start state *s*0 over the input symbol "*a*7", from *s*0 the control moves to *s*7, *s*27 and *s*22 because from *s*0 there are transitions to all the above mentioned states on the input symbol "*a*7". Further, from state *s*7 on input symbol "*b*2" the control moves to state *s*8, from state *s*22 on input symbol '*b*2' control moves to state *s*23 and from state *s*27 it moves to state *s*28 over the input "*b*2". Finally, the transitions are checked from the states *s*8, *s*23 and *s*28 over the input symbol "*c*9", wherein only the state *s*28 has transition to the state *s*29. The state *s*29 is the accepting state because it's represented using double circle and it accepts the input pattern and predicts the soil texture as Sandy clay for the input "*a*7*b*2*c*9". The same pattern is also traced using state by state execution method, in which the path obtained is *s*0->*s*27->*s*28->*s*29 and the corresponding process is represented in Figure 6. Automated model has been validated considering soil textural data set of Jangamakotte and Bhaktarahallipedonds of Kolar district, Karnataka, India. Rajan *et al.* (2014).

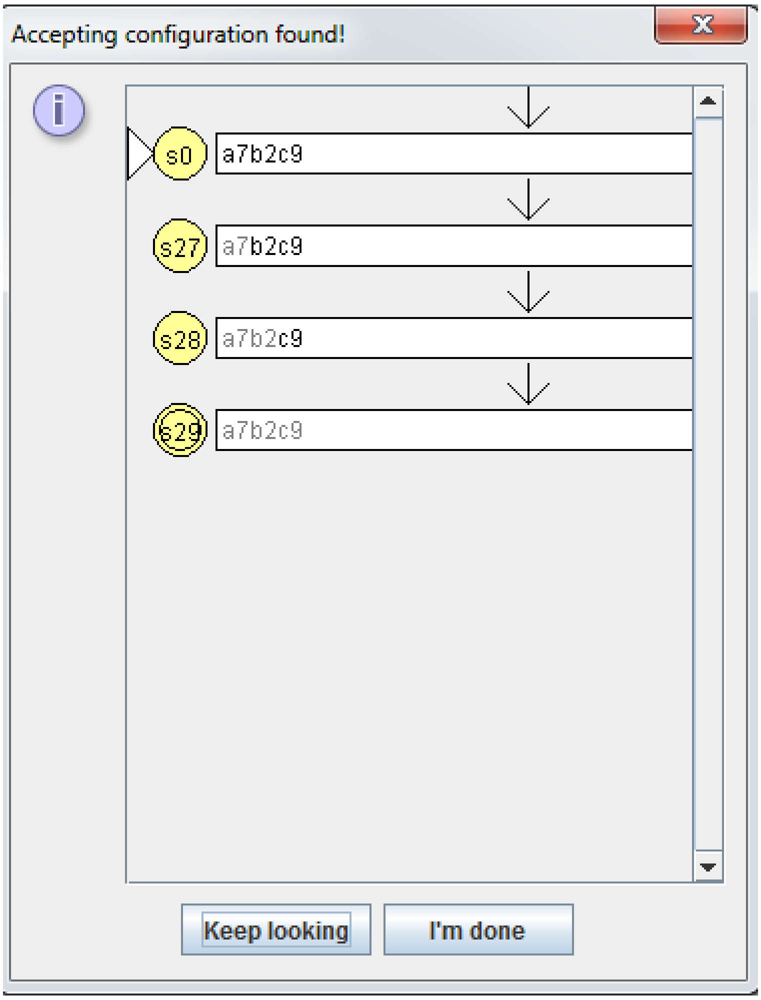

Figure 6: NDFSM model state by state tracing over the input pattern "*a*7*b*2*c*9"

The input pattern "*a*9*b*9*c*9" was tested using automated model which is represented in Figure 7.

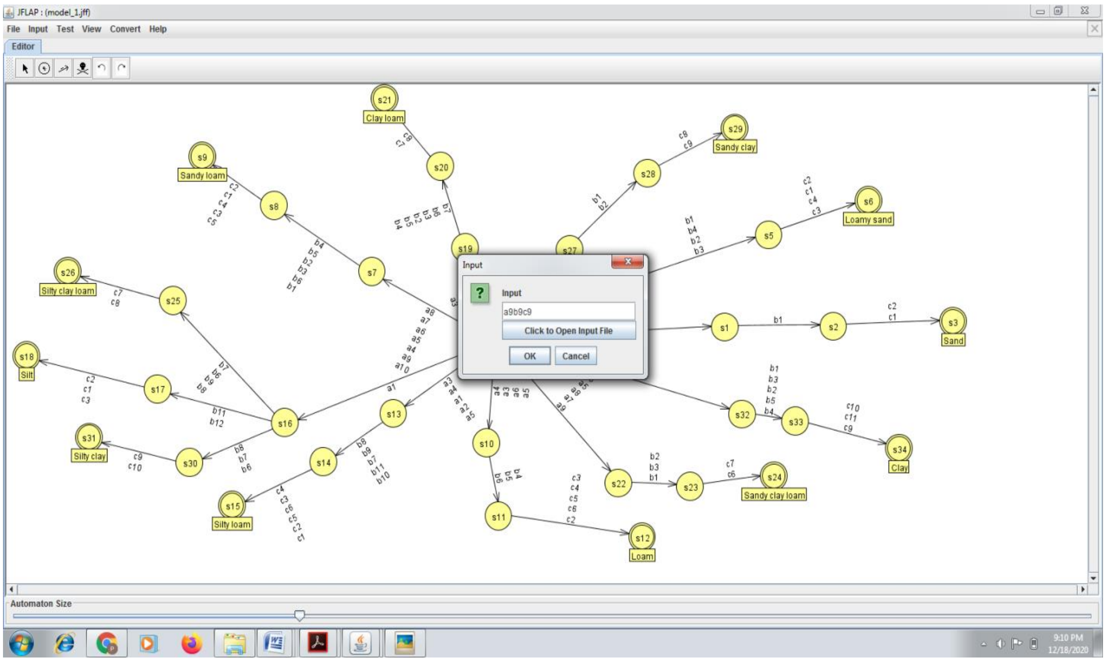

Figure 7: The input pattern *"a*9*b*9*c*9*"* was tested using automated model

The symbol *"a*9*"* of input pattern represents the sand fraction range as 70-80% and the symbol *"b*9*"* of input pattern represents the silt fraction range as 60-73% and also the symbol *"c*9*"* of input pattern represents clay fraction as 40-55%. Suppose if we consider the sample value of sand fraction as 71%, silt fraction as 61% and also clay fraction as 41%, then summation of all there particles size would be 173. For any soil texture sample the summation of sand, silt and clay fraction size must be exactly 100 otherwise the input sample is considered as invalid. The automated model rejected sample input is represented in Figure 8.

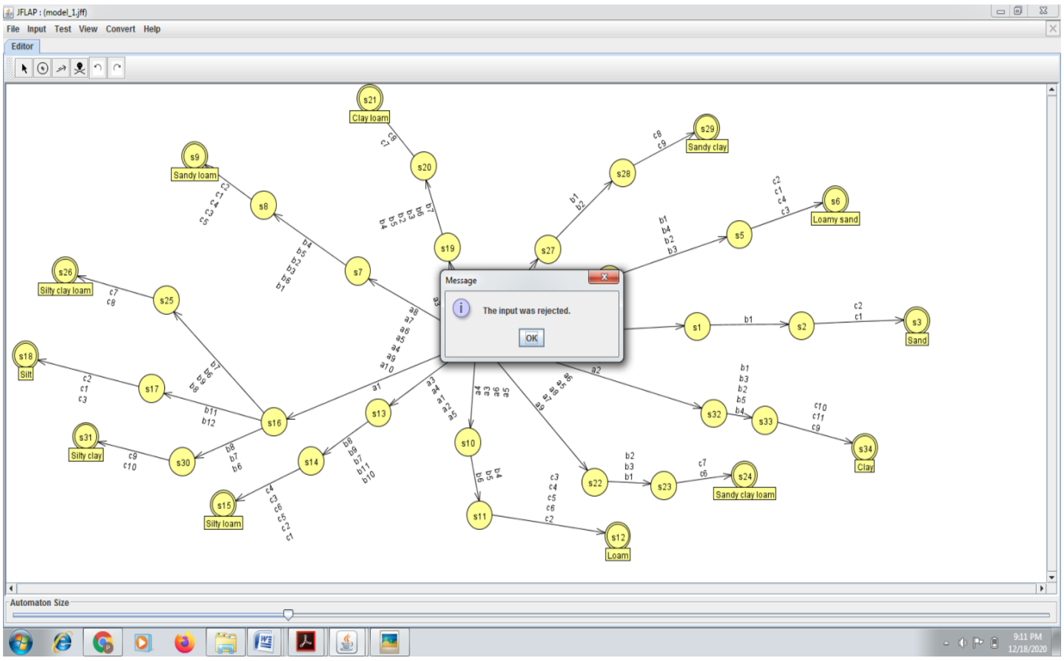

Figure 8: The input pattern *"a*9*b*9*c*9*"* was rejected by automated model

Additionally, multiple soil profile data records can be loaded and predicted at the same time using JFLAP tool and the corresponding details are represented in Figure 9.

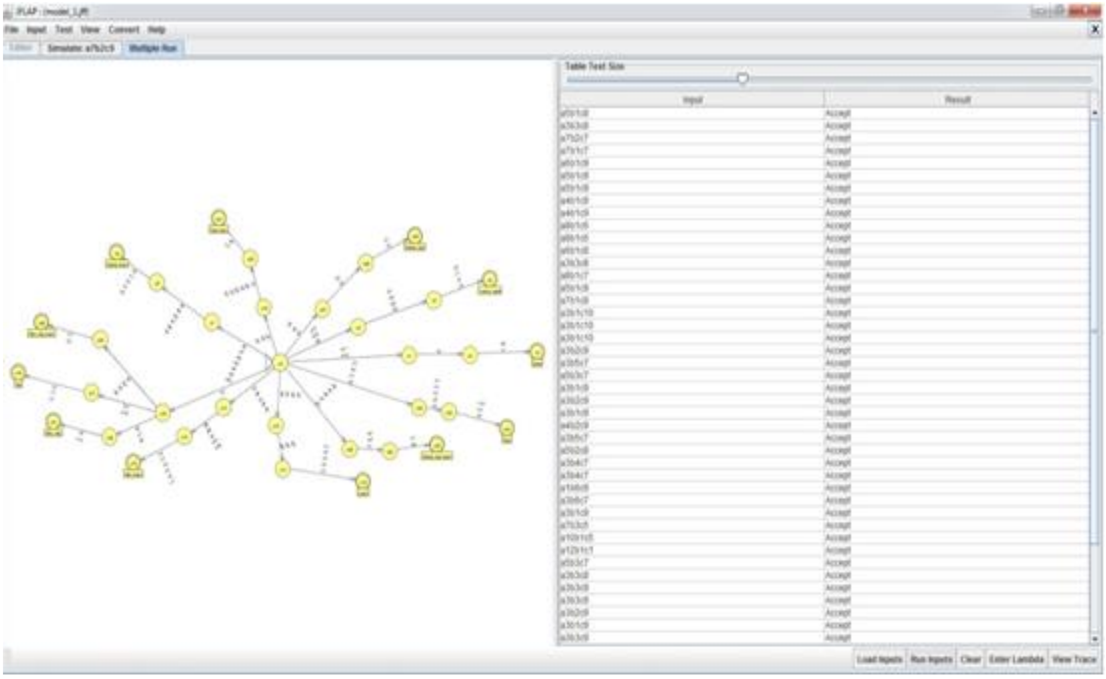

Figure 9: Validation results of automated NDFSM soil texture classification model

4. Conclusion

In this paper the USDA Triangle soil texture classification model is automated using the proposed Non-Deterministic Finite State Machine (NDFSM). The experimental results of NDFSM model exhibited the logical equivalence with USDA triangle model during the testing and validation phase over soil texture classification. The NDFSM soil texture classification model was validated using laboratory tested soil profile dataset. For all the validated patterns the predicted texture of NDFSM model was same as USDA triangle soil texture classification. The proposed automated model simplifies the job of soil texture class prediction.

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