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Self-Learning Problem Prioritization for Operating Tugger Train Systems

Selbstlernende Problempriorisierung für den Betrieb von Routenzugsystemen

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Für die operative Steuerung logistischer Systemen ist der Einsatz von Optimierungsmethoden unter der Nutzung selbstlernender Algorithmen zunehmend Gegenstand von Forschungs- und Entwicklungsaufgaben. Einen besonderen Anwendungsfall bilden an dieser Stelle selbstlernende Wissensmanagementsysteme, welche die zielgerichtete Reaktion auf Abweichungen, also Störungen und Schwankungen von Systemkennwerten, adressieren. In diesem Beitrag wird im Detail darauf eingegangen, wie ein solches System bewerten kann, auf welches in der Regelstrecke vorliegende Problem idealerweise zu reagieren ist. Hierzu werden zunächst vier verschiedene Ansätze hergeleitet und diskutiert. Anschließend erfolgt eine gesamtheitliche Bewertung und eine Synthese der einzelnen Ansätze hin zu einem allgemeingültigen bzw. allgemein anwendbaren Ansatz. Weitere Verbesserungsmöglichkeiten bilden den Abschluss des Papers.

[Schlüsselwörter: selbstlernende Systeme, Leitsysteme, operative Steuerung, Logistiksteuerung, Decision-Making]

For the operational control of logistics systems, the application of optimization methods using self-learning algorithms is increasingly the subject of research and development. Knowledge management systems, which address the specific reaction to deviations, i. e. disturbances and fluctuations of system parameters, form a special application use case. This paper discusses in detail, how such a system can evaluate, which present deviation in the logistic system should ideally be subject to the reaction of the control system. Several ideas are part of the discussion and narrow down to four different approaches. An overall evaluation and a synthesis of the individual approaches to a universally valid and applicable approach follow. Furthermore, future possibilities for enhancement complete the paper.

[Keywords: self-learning systems, control systems, operational control, logistics control, decision-making]

1 FACING DEVIATIONS IN LOGISTICS

Planning technical systems in intralogistics uses different parameters to acquire proper dimensions and restrictions for a planned system. These parameters either are measured or targeted values. Designing the logistics system aims to reliably reach the targeted values during everyday operations.

During ongoing operation, the wide variety of technical systems in intralogistics is constantly subject to fluctuations and disruptions. So, deviations from a planned system behavior seem unavoidable. Reasons for those deviations are e.g. mistakes caused by the personnel, technical failures or misinformation. A detailed discussion of these reasons can be found in [WF20]. The deviations during the operation of a technical system in logistics cause the targeted values of the logistics systems, like economic efficiency, punctuality or other logistical qualities, to differ from the original planning. Especially smaller companies, which operate complex logistics systems, find it hard to reinstall a stable, economical status of the logistics processes, as expertise, and experience of the personnel might not be sufficient. The loss of expertise due to the fluctuation of personnel, especially retirements, add the problem of saving knowledge regarding the systems and processes for future appliance.

1.1 BACKGROUND OF RESEARCH

The research project "MuCRoute – Monitoring and Controlling of tugger train systems" addressed the problem of disruptions and fluctuations in a specific subsystem of production logistics, the tugger train system. The result of the project is the development of a knowledge management system of self-learning character, which enables an automated detection, elimination and solution evaluation in case of deviations in a tugger train system. This self-learning system requires several components. Apart from a key

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figure system, a quantification of correlations between deviations and a database for solutions, especially the decision-making in the several steps from detecting problems to evaluating the effects of applied solutions is a major part of the design process. This paper will address one of the basic questions of such a system regarding decision-making: How can a prioritization of problems look like?

1.2 Addressed questions

While this question of prioritization might appear trivial at first glance, it shows its scope and the associated challenges in a closer analysis. In a logistics system, problems in form of deviations often overlay or even correlate with each other. Therefore, it is important to prioritize the different problems and to identify causes and effects of certain occurrences. The self-learning system should be able to identify the problem, which is either the most urgent, promising to solve or of highest effect. This requires following primarily defined rules.

This paper will outline different approaches to decision-making in order to select the appropriate problem regarding multiple parameters and focuses. Having identified the necessary parameters, a mathematic definition of the individual approaches allows discussing these approaches at a more detailed level, especially regarding the self-learning background. As a conclusion, the paper proposes merging the different approaches to one prioritization rule. This rule allows an individual adjustment of sub factors of prioritization, so that individual appliance might represent the individual needs of the operated logistics system.

2 State of the art in science and technology

The state of the art regarding prioritization rules for problem identification represents two parts. First, a short examination of literature on self-learning systems in logistics shows current appliances and approaches to use artificial intelligence (AI) in logistics. The second part of this chapter discusses sources that are more basic concerning decision-making and prioritization.

2.1 Self-learning Knowledge management systems in Logistics

Knowledge management systems and AI are increasingly subject to discussion and analysis in literature regarding logistics and production management. For many appliances, AI-based functions and approaches allow to enable new functionalities, enhance current possibilities or simply reduce costs. However, only a small proportion of these publications, developments or products are currently addressing the specific task of controlling logistics systems during operation. Following this, the evaluation of tugger trains and their deviations from planned or targeted behavior are also no focus of current literature or even product development. Concerning logistics, this paper will outline three exemplary approaches and ideas, where AI based technology enables self-learning tools and mechanisms.

First to mention are *Bintrup et. al.*, who use AI based analysis for “Predicting Hidden Links in Supply Networks” [BWW+18]. In a related field, *Nikolopoulos et. al.* discuss “Forecasting supply chain sporadic demand with nearest neighbor approaches” [NBB16]. Apart from that, *Więcek* proposes intelligent systems to approach inventory control und uncertainty [Wię16]. None of these projects and examples take use of any prioritization rules for decision-making. Therefore, the question of prioritization approaches is not solved sufficiently for a direct use in self-learning systems.

Even more general evaluations do not address the questions of prioritization regarding intelligent systems in logistics. For example, *Fauland* describes the principles of pattern recognition as the basis of systems [Fau18] and *Günthner et. al.* evaluate the control of logistics processes as a possible field of application under the consideration of a comprehensive digitalization of intralogistics [GH10], but do not discuss prioritization or selection problems in detail.

2.2 Prioritization and decision-making

As far as the known and analyzed literature goes, the question of automatically prioritizing problems occurring in a logistics system is not the focus of current evaluations or projects. Therefore, basic considerations about decision-making and prioritization are a possible starting point of this paper. In literature, multi-criteria decision mechanisms and fuzzy logics are the most common approaches to prioritization. This covers both, automated systems as well as manual approaches. Of course, multi-criteria decision mechanisms cover any part of the industrial-productive environment. [KBY08]; [LGS12]

For the problem prioritization issue, literature describes, the Multiple Criteria-, Multiple Goals-, Multiple Attributes- and Multiple Objectives- Decision-making methods as potentially suitable approaches. These closely related methods share the initial definition of an objective function. This function differs between the methods, as it targets different variables for decision-making. Decision-making is also subject to current discussions and evaluations in literature itself. Regarding the variety of sources, this paper condenses widely cited and recommended sources, as it should give a sufficient overview regarding the ideas, possibilities and restrictions of the decision-making methods. [HY81]; [Rao07]; [Ros11]; [PDK08]

As explained, the decision-making methods for multi-criteria problems can target variables:

- *Criteria* describe a measure for evaluating the effectiveness of a decision on Attributes or Objectives. [HY81]

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- *Goals* are the expression of the absolute targets of a system, which are set either based on external or internal requirements. For example, a minimum level of utilization that has to be achieved in a tugger train system operation. [HY81]
- *Attributes* commonly are directly measurable parameters of a system for decision-making. These express the behavior of the system directly. [HY81]; [Rao07]
- *Objectives* describe higher-level demands for the decision-making process. Objectives are quantified and represented by different Goals and express basic targets of an enterprise or system operator, such as the desire to maximize profitability or minimize error rates. [HY81]

In the context of generating rules for especially self-learning problem prioritization, *Multiple Criteria Decision-making* is the primary approach, as a clear separation and identification of *Attributes, Objectives* and *Goals* is not always possible and therefore not suitable.

3 Development of possible prioritization approaches

As described in the state of the art, self-learning prioritization rules are so far not available or discussed. Thus, chapter 3 describes the basic development leading to four different approaches of prioritization. This covers their introduction and discussion, by applying the basic rules and ideas of chapter 2.

3.1 Field of Appliance

In order to develop suitable strategies and rules for the prioritization of problems, depicting and analyzing the major purpose of the self-learning system is suitable. Therefore, the four steps in a self-learning system reacting to system deviations in logistics are as follows and depicted in figure 1:

Step 1: The knowledge management system detects deviations from target values in the key figures of the tugger train system by reaching or breaking defined intervention limits for the key figures values.

Step 2: The knowledge management system determines the specific pattern in which the key figures deviate. Known deviations for comparison are stored using the correlating key figure pattern as a typical characterization and can be identified in this way by alignment.

Step 3: The knowledge management system has identified, which deviations exist in the system and selects a deviation for counteractions based on the strategies developed in this paper.

Step 4: The knowledge management system applies solution strategies for the identified problem to the application and observes their success.

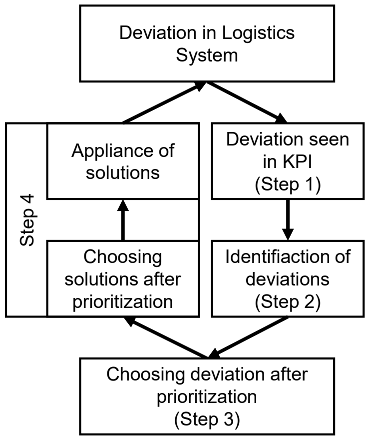

Figure 1. The mechanisms behind the self-learning system to correct deviations (reduced version)

As this paper intends to address the prioritization of problems and the following decision-making, the fundamental issue and topic of this paper lies in step 3. Other questions regarding the self-learning knowledge management system have been or will be subject to further detailed elaborations. In the following, this paper presents and evaluates strategies for selection.

3.2 Specific rules for Prioritization

The following subchapters will each represent and discuss one approach to problem prioritization. After describing the approach “strongest deviation”, possible rules after costs, time and criticality follow.

3.2.1 Strongest deviation rating

A very intuitive approach to selecting a problem is, to rank the occurring deviations by their intensity. After that, the strongest deviation will be matter of further actions. To do so, in the first place, a logical function has to be defined that allows the identification of the strongest deviation. Since the different deviations use different amounts of key figures for representation, the further problem of a generally valid and comparable classification of the results arises.

In order to meet these requirements, the approach calculates the average deviation of all concerned key figures for each existing problem. To do so, all key figures are percentage values representing the deviation of a key figure from a target or average value. According to this definition, the mathematical description for selecting a problem after the strongest rating follows this formula:

$$d_a = \max_j \left(\frac{1}{n_j} \sum_{i=1}^{n_j} \left| a_{ij} \right| \right) \tag{1}$$

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Where

d_a is the evaluation of the largest deviation by strength

a_{ij} is the percentage deviation of kpi i regarding deviation j from target or average value

n_j is the number of key figures assigned to deviation j

On one hand, the advantage of this evaluation is that the entire intensity of a deviation is included in the evaluation. This ensures that individual, particularly strongly deviating values of individual key figures are represented in the evaluation. On the other hand, the effects of this greater deviations on the result of the approach are over all dampened by other key figures of smaller deviation intensity. This serves to prevent an overreaction of the knowledge management system and to allow a stable correction process.

The problem with this form of decision-making is that this weighing does not represent the later effects of the deviations. Thus, there is a risk that the system reacts to a deviation, which is strong, but its effects would be negligible. As a result of that, a very problematic deviation might not be addressed when necessary.

3.2.2 Downtime costs due to system deviation

As described at the beginning, deviations in the form of fluctuations and failures usually lead to a loss of economic efficiency. Examples can occur in the form of lower process efficiency, increased wear or failure costs. For this reason, the monetary evaluation of a failure is proposed using the following mathematical description.

$$d_m = \max_j(m_j) \tag{2}$$

Where

d_m is the evaluation of the largest monetized deviation

m_j is the monetized damage assessment of the deviation j

A monetized assessment of the damage, caused by a deviation, allows to address the deviation of the most severe economic damage for prioritized remediation.

While the monetized assessment enables benefits regarding cost effectiveness during operational use, the required configuration of the knowledge management system requires relatively extensive preparation. During this preparation, a cost evaluation for possible deviations has to take place and must be part of the implementation of a knowledge management system. Coping with unknown deviations also requires the evaluation of damage patterns as well as corresponding cost rates.

Furthermore, the solitary evaluation of the damage costs due to the deviation alone does not allow a complete monetized verdict. Such a decision would also require knowing the costs and efforts of the possible solutions. Strategies to evaluate solution costs are subject to further research activities.

3.2.3 Time until return to stable system state

Another possibility of prioritization is the question, how fast a solution for deviations can be in place. In this case, the decision criterion is not the question of the effects of malfunction effects, but the time it takes to correct them. This information regarding timespans for correction comes from experience or previously estimated values. Especially in logistics systems with strong dependencies and interconnections, the time necessary to return to a stable system state is of high importance. Therefore, the mathematical expression of this rule includes a simple formula for a determination of the minimum time to return to the stable system state.

$$d_t = \min_j(t_j) \tag{3}$$

Where

d_t is the evaluation of the deviation regarding shortest time to solve

t_j is the known or expected rectification time for the deviation j

The problems of the implementation of this approach correspond to the weaknesses of the cost driven one. As for costs, also time components require a prior estimate and previous calculation during, respectively for, implementation.

3.2.4 Criticality of the deviation

The evaluation mechanisms based on the strength of the deviation, on costs or timespans have the common weakness that the complete and detailed impact on the logistics system remains unevaluated and thus unconsidered. The fourth approach explicitly addresses this issue. For the implementation of a self-learning knowledge management system in logistics, it is usually also necessary to assess in advance, which deviations or disturbances are more critical than others are. In specifically conducted surveys, these criticalities were primarily disruptions that would have triggered a stop of a single process step or a complete halt of the supply chain. Other than the costs approach, this idea also depicts qualitative risks and does not require a complete monetized quantification.

Thus, the fourth prioritization approach uses the quantified criticality of a deviation as criterion. With the intention of including the effects of a deviation in this prioritization approach, these effects need to be a specific part of the mathematical description. During operation, the knowledge management system determines how many effects are conjugated to a deviation and adds their average criticality to the criticality of the triggering deviation. The average value is used, to achieve a comparable factor. Otherwise, deviations with few but extreme effects could imply a lower rating then deviations with many effects of low criticality. The conjugations of causes and effects are part of the knowledge management system and therefore a necessary part of implementation.

$$d_c = \max_j \left(c_j + \left(\frac{1}{e_j} \sum_{k=1}^{e_j} w_{kj} \right) \right) \tag{4}$$

Where

d_c is the evaluation of the largest deviation regarding criticality

c_j is the criticality of the deviation j

e_j is the number of effect phenomena assigned to deviation j

w_{kj} is the criticality w of the assigned effect phenomena k to deviation j

Two points show the major advantage of this approach to prioritization. First, as already described in the requirements, the criticalities of the effects of deviations are a major part in the evaluation. Second, the results of the prioritization do not as much depend on estimates regarding costs or timespans and in this respect are relatively more objective. At the same time, the fact that criticality has to be preassigned by user input is the main disadvantage of the approach. The possible values for criticality depend on individual experiences of users and are hardly measurable. During operation of the knowledge management system, the criticality, costs and timespans might become easier to evaluate over time, as the system learns and expands its experience.

3.2.5 Evaluation and possible application principles

Discussing the different prioritization rules shows, that a clear favoring of one particular rule is not possible. Under the aspect that the rules should be independent from subjective assessments, none of the approaches is completely suitable. Two approaches use estimates on costs and timespans, two others require either target values or predefined criticality. In order to design a mixed approach, it is necessary to outline the different pros and cons of the approaches.

First, the approaches of criticality and strength utilize the effect, that prediction needed for their implementation are anyway necessary for the implementation of the knowledge management system in logistics. During planning of the logistics system, the definition of target values is obligatory to find proper system dimensions. In that way, the comparison values to determine the strength of a deviation already exist. Second, apart from the mere target values regarding efficiencies or other key figures, also possible deviations and system failures are subject to examinations during planning. However. the examinations of possible failures and deviations needs to exceed the common dimensions, as the planning process has to cover questions of criticality and cause and effect networks in the planned system. In case of introducing a self-learning knowledge management system to an already existing system, these questions drop in difficulty and complexity due to already existing experience.

The main difference regarding the rules of costs and timespans is the usage of measurable values. Although these values are only be estimates at the beginning of the self-learning process, due to the improvements by self-learning the values will get more and more precise and resilient. While the approach using costs requires valuating incurred damages by cost rates and resulting financial efforts, the timespan approach does not use external measurement. The time until solving the deviation is measureable by investigating the key figures and stating, when the operating system is stable again.

In conclusion, a singular selection between the four individual approaches is hardly reliably possible without prior estimation of the logistics systems behavior. For each of the individual approaches, a corresponding learning phase of the knowledge management system is necessary, which must confirm or concretize assumptions made during designing. A consequence of the rigid selection also is that the knowledge management system might optimize only the chosen parameters, which are part of the prioritization rule. A change of approaches then results in a repeated learning phase.

4 Developing a universal Approach

As mentioned, the different approached standing alone do not sufficiently describe proper prioritization approaches. The following chapter shows a possible solution to this problem and presents further thoughts towards future developments and opportunities.

4.1 Synthesis of the Approaches

In order to define one universal approach, this chapter will show, how merging the different rules into one formulation is possible. The target of this merging is, to utilize the different advantages of the single approaches so that their drawbacks annihilate each other as far as possible.

The *Simple Additive Weighting (SAW) method* and the *Weighted Product method (WPM)* allow to develop the necessary mathematic algorithms. For the development of individual rules, these allow to combine different individual criteria, either additively or multiplicatively, depending on the individual use case. Also, they allow the implementation of weighting factors to adjust the influencing variables and their interaction. This is necessary to design comprehensive approaches regarding comparability and calculateability. [Mac68]; [HY81]; [BH08]; [Eas75]; [Sea62]

The four approaches, strength, costs, timespans and criticality, each represent one block, which requires the definition of a weighing factor and furthermore, normalization. Furthermore, as the approaches are normalized for better comparability, the additive approach is in use.

The weighing factors allow an individualized and dynamic setup of the prioritization. Individual, as the weighing uses adjusted factors for each of the single rules. The factors depend on the specifications introduced during planning by the designers of the system. Dynamic, as these factors can be subject to external reconsideration over time reacting to changing circumstances or targets.

For an implementation of the holistic approach of prioritization as a unified mathematical expression, it is necessary to normalize the results of the four presented individual terms. While the approach of the strongest deviation already represents a percentage value, the monetary approach produces a monetary value and the temporal approach an absolute timespan. The result of the criticality evaluation depends on the specifically selected evaluation scale of the systems implementation. In order to achieve a normalization, a comparison value is necessary.

Wherefore, this prioritization rule utilizes the fact, that an examination of all four approaches is necessary. Thus, for every approach a maximum or minimum value exists between the different deviations depending on the prioritization approach. This maximum or minimum value is the comparison value. In most cases, these maximums or minimums will not be represented by one deviation but spread over the different problems. In that way, up to four benchmarks of approach specific prioritization exist. Now, it is possible to select every deviation against these four benchmarks and this allows evaluating, which deviation has the minimum gap to the optimum prioritization over all approaches. Scaling the maximum prioritization of each approach to 100 %, the individual results are always mathematically secured between 0 and 1 and therefore completely comparable.

The corresponding expression including the weighing factors is as follows. The subcomponents are as presented above in chapter 3 in formulas (1) to (4):

$$d_j = z_a \frac{\left(\frac{1}{n_j}\sum_{i=1}^{n_j}\left|a_{ij}\right|\right)}{\max\limits_p\left(\frac{1}{n_p}\sum_{i=1}^{n_p}\left|a_{ip}\right|\right)} + z_m \frac{m_j}{\max\limits_p\left(m_p\right)} + z_t \frac{\min\limits_p\left(t_p\right)}{t_j} \tag{5}$$

$$+z_c \frac{\left(c_j + \left(\frac{1}{e_j}\sum_{k=1}^{e_j} w_{kj}\right)\right)}{\max\limits_p\left(c_{i\ldots n} + \left(\frac{1}{e_{i\ldots n}}\sum_{k=1}^{e_{i\ldots n}} w_{k,i\ldots n}\right)\right)}$$

With $\quad 1 = z_a + z_m + z_t + z_c$

Where

- d_j is the evaluation of the prioritized deviation j
- a_{ij} is the percentage deviation of kpi i regarding deviation j from target or average value
- n_j is the number of key figures assigned to deviation j
- m_j is the monetized damage assessment of the deviation j
- t_j is the known or expected rectification time for the deviation j
- c_j is the criticality of the deviation j
- e_j is the number of effect phenomena assigned to deviation j
- w_{kj} is the criticality w of the assigned effect phenomena k to deviation j
- z_a Weighting of the "strength of deviation" prioritization dimension
- z_m Weighting of the monetized prioritization dimension
- z_t Weighting of the temporal prioritization dimension
- z_c Weighting of the prioritization dimension "criticality of deviation"

As described, prioritizing the selection with the help of this rule allows the user or system manager to weigh the approach individually. As the self-learning knowledge management system monitors all solution parameters, it also gathers experience regarding all the different parameters of the prioritization. As a result of this, the selection behavior is improved in all four parts of the combined approach, which enables shifting the weighing factors without an additional learning phase.

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4.2 Time-depended weighing as future option

A future option regarding the weighing factors is, to design their value dependent of either the operating time since implementation or the number of corrected deviations. The idea behind this option is, to exploit the development of the knowledge in a self-learning system and therefore improve the rules behind decision-making and prioritization. As explained, the different parts of the combined prioritization approach have advantages and disadvantages regarding the phase of appliance and running time. As the approaches of strength and criticality do not require as much experience of the system, as costs and timespans, it is favorable to weigh those two approaches higher in the early operations of the self-learning system. Over time and with experience in the system, the weight can shift towards costs and timespans.

In order to define such rules, it is necessary to find possible markers for the point, where a change in weighing is advisable. The exact definitions for these rules are currently up to consideration and further development.

5 Conclusion And Outlook

The discussion of the prioritization approaches and with a concluding evaluation of the results and short outlook towards future options in development.

5.1 Concluding evaluation

This paper discusses four possible approaches to enable self-learning systems in logistics regarding decision-making. The focus of the discussion hereby lays at the question, which deviation in a logistics system should be subject to correction. The four approaches each have characteristic advantages and disadvantages, which allow the conclusion that none of them is suitable as a singular option. Therefore, a combination of the different approaches to one major rule is the proposed solution, using the methods of multi-criteria decision-making in the process. In this step, weighing factors and normalization add better comparability and individualization to the suggested approach. As shown, further developments in the future regarding self-learning adjustment of the weighing factors are promising possibilities.

Although the different approaches and their combination are well discussed and so far ready for use, tests in form of practical application have not taken place at this point. The accompanying research project is equipped for a usage of the combined rule, but will be limited to the single approaches in the first phases of testing. Because of that, a full evaluation of the proposed ideas is still open. Nevertheless, the theoretical background is discussed with appliers and programmers as well as experts of logistics. Results of these discussions and first laboratory tests are promising.

5.2 Further Development

Of course, the prioritization approaches allow different further ways of development and enhancement. Two ideas follow here.

One possibility for further optimization of the approaches and the algorithmic regularities is the use of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach for the calculation of the deviations. In contrast to the used calculation rules, TOPSIS allows an estimation of the deviation from a minimum and a maximum value equally and thus represents a relativized view of the selection strategies [Ros-2011]. However, at the state of the presented discussion, a detailed discussion of this approach is pending. The introduction of TOPSIS might be a solution in case of a great number of overlapping deviations and will be discussed therefore under a specific evaluation.

Regarding the process behind the idea of self-learning knowledge management systems in logistics, a second field for decision-making exists. While this paper depicts the way of choosing a problem to solve, rules for selecting the best suiting solution are also necessary. Although these rules might be related to the ones depicted in this paper and seem very similar, their motivation and discussion covers very different questions and problem. Therefore, research regarding these rules will be subject to upcoming publications.

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