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Integration of Geomagnetic Activity Monitoring Data Processing Methods and Smart City Technologies to Ensure the Required Safety of Unmanned Transport Infrastructure Objects

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Abstract: Amid the rapid development of the Smart City concept, grounded in the integration of information technologies and the Internet of Things, unmanned transport infrastructure objects (UTIO), such as drones and autonomous vehicles, are becoming integral to multimodal transportation systems. However, geomagnetic disturbances (GMD) caused by solar activity disrupt GNSS functionality, reducing positioning accuracy to several meters and posing risks to UTIO safety in high-traffic urban environments. This study proposes an approach combining GMD monitoring data analysis with Smart City management systems. Algorithms for real-time UTIO navigation adaptation, including route correction using inertial navigation systems (INS) and mathematical models of GMD impact on GNSS, were developed. Computer simulation of a transport network with 10,000 UTIO demonstrated a 60% reduction in incidents at Kp > 5 compared to conventional methods. The findings highlight the importance of accounting for space weather to enhance UTIO movement reliability and safety in Smart Cities, showcasing the proposed approach's superiority over existing solutions that neglect GMD effects.

1 INTRODUCTION

The "Smart City" concept is a rapidly evolving and widely implemented framework for urban development and management, relying on the integration of information and communication technologies and the Internet of Things (IoT). Smart Cities support multimodal transport, including unmanned transport infrastructure objects (UTIO) such as drones and autonomous vehicles (Ng et al., 2021). UTIO functioning is carried out in real-time mode, therefore high requirements on operational reliability are imposed on their control systems, which cannot be ensured without organization of stable high-quality communication with UTIO. Amid increasing urbanization, the integration of Smart Cities with UTIO highlights the critical need to ensure their safe operation. The rapid proliferation of UTIO, managed by Smart City systems, necessitates the development of control methods that account for external threats, including geomagnetic disturbances (GMD) (Hanane A, 2023). The characteristics of the GMD are determined by the properties of the solar wind and the interplanetary magnetic field interacting with the Earth's magnetosphere.

GMD, triggered by solar activity, can significantly impair the accuracy of navigation systems reliant on Global Navigation Satellite Systems (GNSS), posing risks to UTIO functionality. This is particularly critical in Smart Cities, where high traffic density and complex infrastructure demand precise control.

This study proposes an approach based on integrating GMD monitoring data analysis with Smart City. Algorithms were developed and implemented as software for real-time UTIO navigation adaptation, including route correction. Computer simulation results demonstrate a reduction in incidents by at least 60% when employing the proposed approach, underscoring the importance of accounting for space weather in UTIO operations. Thus, the proposed method enhances the reliability and safety of UTIO movement under GMD conditions.

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2 STATE OF THE ART

Recent advances in Smart City technologies and UTIO drone control have demonstrated significant progress in integrating Artificial Intelligence (AI) and Io solutions to improve transportation safety in urban environments. Current research trends are mainly focused on three main areas: (1) developing multi-level traffic management systems, (2) improving GNSS positioning accuracy under different environmental conditions, and (3) mitigating the effects of space weather on autonomous navigation systems as part of UTIO. However, despite these advances, critical gaps remain in addressing the impact of GMD on UTIO performance in Smart City ecosystems.

2.1 Smart City Traffic Management Systems

Modern approaches to UTIO management in Smart Cities increasingly rely on AI-driven solutions and IoT networks. In (Mohammed et al., 2014), unmanned aerial vehicles (UAV) were considered for monitoring traffic in urban environments and established the principles of real-time traffic data collection. Subsequent studies by Afrin et al. (2024) developed a three-layered framework incorporating:

1. “Perception layer”: Sensor networks for real-time data acquisition
2. “Communication layer”: 5G/V2X infrastructure for low-latency data transfer
3. “Decision layer”: AI algorithms for traffic flow optimization

While these systems demonstrate impressive adaptability to conventional urban challenges (e.g., congestion, accident prevention), they notably lack integration with space weather monitoring systems. This omission becomes critical during geomagnetic storms when GNSS positioning errors can exceed 10 meters (Xue et al., 2022), rendering standard traffic management protocols ineffective.

2.2 GNSS Vulnerability to Space Weather

Contemporary research has extensively documented the effects of ionospheric disturbances on satellite navigation:

- “Single-frequency receivers” experience up to 30% signal degradation during moderate geomagnetic activity (*Kp* = 4-5) (Oladipo & Schüler, 2012);
- “Dual-frequency systems”, while more resilient, still show 5-15 meter errors during severe storms (*Kp* $\geq$ 7) (Etchells et al., 2024)
- “Signal scintillation” causes complete GNSS outages in high-latitude regions (Dongsheng, et al., 2024)

The Total Electron Content (TEC) model (Equation 1) remains the standard for quantifying ionospheric delays, yet its implementation in real-time UTIO navigation systems remains limited. Current Smart City infrastructures typically employ post-processing TEC corrections, creating dangerous latency for autonomous vehicles operating in dynamic urban environments.

The above emphasizes the critical need for the integrated approach proposed in this study, which combines Big Data processing of geomagnetic observations (Korobeinikov, 2021) and adaptive Kalman filtering (Cheng et al., 2024) to create a robust solution for UTIO security during GMD.

3 RESEARCH METHODS

The proposed approach includes the following components:

3.1 CMD Data Collection

GMD monitoring utilizes data from variation station networks, the International Real-Time Magnetic Observatory Network (INTERMAGNET) (Korobeynikov 2024), and geostationary satellites, such as those provided by NOAA (National Oceanic and Atmospheric Administration - https://www.noaa.gov/). The *Kp* index, which quantifies geomagnetic activity levels, serves as a key parameter for assessing GMD impact on GNSS. *Kp* values can be sourced, for example, from IZMIRAN (http://spaceweather.izmiran.ru/eng/currents.html), where in the process of daily forecasting all available data, both those obtained in IZMIRAN and from numerous information resources provided on the Internet, are analyzed and stored in databases. On the basis of the developed models, methods of forecasting various aspects of space weather for different periods of time have been created.

3.2 Big Data

Due to the complex internal structure, strong variability, irregularity and large volume of data recorded by GMD, the task of processing and analyzing them is quite challenging. The proposed approach applies methods based on the Big Data concept (Korobeynikov 2021).

3.3 Mathematical Model of GMD Impact on GNSS

GNSS are subject to the disturbing effects of physical conditions in near-Earth space. Thus, the accuracy of navigation systems using very low frequency signals (LORAN, OMEGA) depends on the knowledge of the actual height of the lower boundary of the ionosphere. Rapid vertical changes in this boundary during solar flares and magnetic storms can introduce errors on the order of several kilometers in the determination of locations. In a highly perturbed ionosphere, loss of GPS/GLONASS global navigation system signals can occur. Thus, the use of GNSS data to achieve the required accuracy requires a good supply of information on space weather conditions to avoid the resulting errors.

The mathematical model of GMD effects on GNSS accuracy is based on the ionospheric signal delay equation involving Total Electron Content (TEC) (Oladipo et al., 2012):

$$\Delta t = \frac{40.3}{cf^2} \cdot TEC \quad (1)$$

where: Δt — signal delay (s); c — speed of light (m/s); f — GNSS signal frequency (Hz); TEC — total electron content (electrons/m²), dependent on GMD; 40.3 — dimensional coefficient [Hz], corresponding to the critical frequency.

At high Kp values (Kp > 5), TEC increases, leading to positioning errors of 5–10 m.

3.4 Mathematical Model of UTIO Movement

The dynamics of UTIO motion is described by the following equation:

$$r(t) = r_{true}(t) + \Delta r$$

where: $r(t) = [x(t), y(t), z(t)]$ — observed spatial position of the UTIO; $r_{true}(t)$ – true position; Δr – error due to GMD.

For correction, an inertial navigation system (INS) based on the mathematical model (1) is proposed:

$$r_{corrected}(t) = r(t) + K \cdot \left(r_{INS}(t) - r_{GNSS}(t)\right)$$

where K — Kalman filter matrix (Cheng et al., 2024); $r_{INS}(t), r_{GNSS}(t)$ - position obtained by INC and GNSS, respectively.

Correction of the location coordinates (system state) using the Kalman filter, which is a recursive filter, allows us to determine the optimal estimate of the system state in dynamics, taking into account the noise in the data and previous information about the system state.

3.5 Mathematical Model of UTIO Collision Probability

UTIO collision analysis plays a very important role for the safety of UTIO traffic control, because any collision causes various kinds of losses. In this project, the probability of a UTIO collision is calculated using the following formula:

$$P = 1 - \alpha e^{-\lambda \Delta r^2}$$

where: λ — UTIO density per unit area (UTIO/m²); α — coefficient.

The probability value in this model depends nonlinearly on the magnitude of the UTIO density and the square of the UTIO location calculation error given by the GNSS and dependent on the GMD. Thus, the simple presentation of the formula for calculating the probability hides the complex relationship between different factors.

3.6 Smart City UTIO Management Algorithm

An algorithm has been developed to control Smart City UTIO, the generalized steps of which are:

- **Step 1**: Collect real-time GMD data.
- **Step 2**: Estimate GNSS error based on calculated signal delay Δ*t*.
- **Step 3**: Adjust UTIO routes using INS and ground sensor data.
- **Step 4**: Redistribute traffic in high-*Kp* zones (*Kp* > 5) by altering movement priorities or temporarily suspending UTIO operations.

4 SIMULATION

When conducting scientific and practical research, computer modeling is currently one of the main tools for cognition of the world. For example, with the help of computer modeling it is possible to assess the impact of various effects of the presented approach in a megacity. Computer modeling combines low research costs and high efficiency.

To validate the approach, a Smart City transport network with 10,000 UTIO was simulated. Scenarios included moderate conditions (Kp = 3) and severe GMD (Kp = 7). A simplified hash function generated movement trajectories.

4.1 Result

The following results were obtained as a result of the calculations performed by computer modeling:

4.1.1 Positioning Accuracy

At *Kp*=3 (moderate GMD): Without correction: mean GNSS error = 1.46 m, standard deviation (SD) = 0.29 m; With INS: mean error = 0.48 m, SD = 0.14 m (Figure 1).

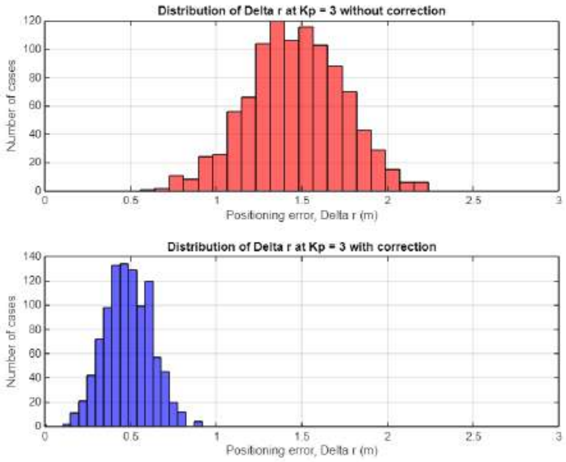

Figure 1: Distribution of positioning errors at *Kp* = 3.

At *Kp*=7 (severe GMD): Without correction: mean error = 7.85 m, SD = 1.6 m; With INS: mean error = 2.6 m, SD = 0.54 m (Figure 2).

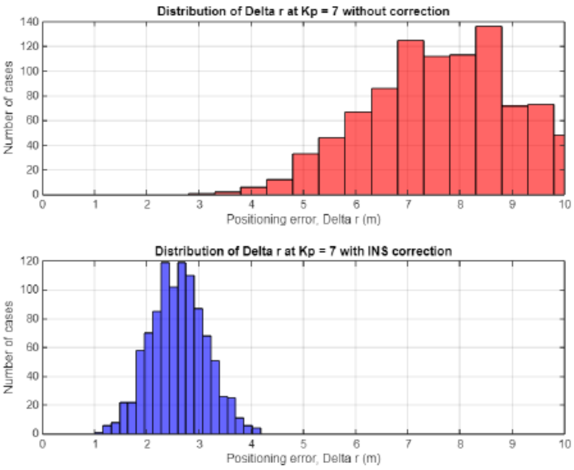

Figure 2: Distribution of positioning errors at Kp = 7.

4.1.2 Movement Safety

Figure 3 presents simulation results of UTIO collision counts as a function of magnetic storm intensity (NOAA G1–G5 scale) with and without INS. During severe storms (G4, corresponding to *Kp* = 9), an average of 8 collisions per hour occur without INS, reduced to 3 with INS.

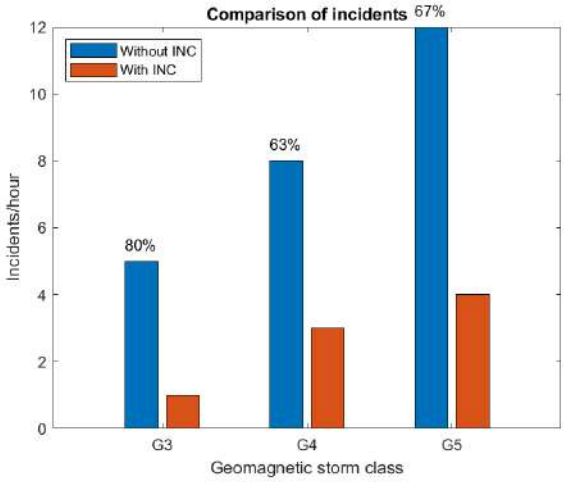

Figure 3: Comparison of incidents.

4 CONCLUSIONS

Simulation results confirm that integrating GMD monitoring data into Smart City management systems enhances UTIO traffic safety and reliability. Data visualization and statistical analysis validate the approach's effectiveness. The proposed Smart City management method ensures the required safety of UTIO movement under GMD conditions, minimizing GNSS-related risks and improving transport infrastructure resilience. Compared to existing methods like (Afrin et al., 2024), this approach offers superior adaptability. It can be integrated into UTIO traffic management systems and enhanced with weather data for greater accuracy. Future research could focus on algorithm optimization and real-world urban testing.

Thus, the proposed approach related to the integration of GMD monitoring data with Smart City's UTIO control technologies represents a critical direction in ensuring transportation safety and reliability of UTIO traffic.

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